Essays on Pricing and Speculation in Commodity Markets

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Introduction

Commodity markets are a crucial sector of the real economy of each nation. In addition, there is a viable derivatives market in which participants trade both for hedging and speculative purposes, especially given the recent entry of investment banks and hedge funds. These new participants have become increasingly active in commodity markets at the same time when a boom and bust occurred in commodity prices around the financial crisis 2007/08. This led to growing interest in research, politics, and media, who question the role of speculators and index traders in commodity markets. Since 2008, the number of published articles about the impact of speculation and index trading on pricing in commodity markets has considerably risen. These studies examine whether speculators or index traders influenced commodity prices in a way that led to the excessive movements during the financial crisis 2007/08 or possibly decoupled commodity futures prices from their fundamental value. However, findings lack unequivocal evidence on the role of speculators and index traders on pricing in commodity futures markets. The explanatory power of these studies suffers from data limitations and methodological weaknesses, which impede to find clear causalities. This thesis aims to contribute to the field of "Pricing and Speculation in Commodity Markets" by applying new methodologies and by providing new approaches. Thereby, it attempts to give further insight whether commodity prices actually decoupled from their fundamentals for reasons of speculative and index trading activity.

The first study „The Impact of Speculation on Precious Metals Futures Markets" (co-authored by Elina Pradkhan) analyzes the impact of speculative activity on precious metals' futures returns and volatility. While a large number of studies examine the impact of speculative activity in energy or soft commodity markets, precious metals are rarely considered. Mutafoglu et al. (2012) examine whether precious metals' spot prices can be forecasted by traders' positions in futures markets. Fassas (2012) analyzes the impact of investment flows in exchange-traded products on precious metals' spot prices. Since trading in futures markets is expected to influence futures prices first, we focus on the direct impact of speculative activity on returns and volatility in precious metals' futures markets. The impact of speculative activity on precious metals' futures markets is measured by distinguishing between short- and long-term dynamics, and volatility. All models take into account macroeconomic factors and hedging pressure.

Our results demonstrate that speculative activity does not affect precious metals' futures prices in the short run. However, long-term dynamics of speculative activity influence precious metals' futures returns on a monthly base. In particular, this holds true for gold and silver. Moreover, the magnitude of the monthly based long-term impact on gold and silver more than doubled from the first (January 2000 to June 2006) to the second subperiod (June 2006 to December 2013). Longer time horizons, bi-monthly and quarterly, offer weak evidence for an impact of speculative activity on precious metals' futures returns. With respect to platinum, the impact of speculative activity on the conditional variance stabilized in the second subperiod. In the palladium futures market, a destabilizing impact can be observed in the first subperiod. The de-stabilizing effect of speculative activity is present in the gold and silver futures market during the first subperiod, yet to a much lower degree.

The second study „Price Discovery and Trading Activity in Commodity Futures Markets" (co-authored by Elina Pradkhan) examines how trading activities of different market participants influence the contribution of the futures market to price discovery and the rate of convergence between spot and futures markets for 16 selected commodity futures markets. The relationship between spot prices and futures prices is frequently examined in single commodity markets, mainly for metals and soft commodities. Contrary to former approaches, we analyze the relationship between spot prices and futures prices by including commodities of all subgroups (energies, metals, and softs). Having a large number of commodities, it is possible to cross-sectionally analyze if trading activity has an impact on the contribution of futures markets to price discovery and the rate of convergence between spot and futures markets.

The results from the cross-sectional regression show that the trading activities of different market participants do not significantly contribute to price discovery in commodity futures markets. On a yearly base, trading pressure of hedgers (net short positions) and speculators (net long positions) positively influences the futures markets' contribution to price discovery. Since the degree of the positive impact is similar for hedging and speculative pressure, we assume that it is the interaction between hedgers and speculators that positively contributes to price discovery in futures markets. Considering the rate of convergence between spot and futures prices, we find that speculators improve while index traders impair the rate of convergence.

The third study „The Impact of Market Participants' Interaction on Futures Prices: Comparing Three U.S. Wheat Futures Markets" analyzes the impact of the market structure on wheat futures prices. Several studies examining the impact of speculative activity or index trading on commodity prices solely focus on the relationship between speculators' or index traders' positions and commodity prices among different commodities (see, e.g., Sanders and Irwin, 2011; Aulerich et al., 2013; Irwin et al., 2009). Therefore, important commodity-specific factors are ignored such as the role of supply and demand of a commodity or macroeconomic indicators. I focus on wheat, for which three species with different futures contracts exist: soft red winter wheat, hard red winter wheat, and hard red spring wheat. First, the fundamental development of the three considered wheat species is compared. As price developments of hard red spring wheat futures, in contrast to the other two wheat species, are not justified by the fundamentals, the different market structures of the three wheat futures contracts are analyzed by the Disaggregated Commitments of Traders (DCOT) report. The DCOT report splits all market participants of futures markets into five trader categories. The impact of different market participants and their interaction is analyzed by using a model that also takes into account other factors influencing the wheat futures price; i.e. the U.S. dollar exchange rate, the oil price, and the equity market.

The findings reveal that the price of hard red spring futures did not decouple from its fundamental development for reasons of speculative activity. The dominant presence of commercials, i.e. physical traders, who engage in commercial activities of the commodity, combined with a low participation of other traders led to the decoupling of futures prices. Thus, the detailed comparison of the three wheat species demonstrates that the market structure of commodity futures markets is of great importance for pricing.

The fourth study „The Information Content of Fundamental News vs. Traders' Positions on Grain Futures Markets: Evidence from WASDE and COT Reports" analyzes the impact of fundamental news on corn, wheat, and soybean futures prices compared to the impact of the publication of traders' positions from the Commitments of Traders (COT) report. One advantage of an event study approach is that price reactions in futures markets are examined on a daily base and that the analysis is not restricted to the weekly data from the COT report. Additionally, an event study for this purpose overcomes another weakness faced by most related studies: the importance of fundamental data for commodity prices. While most studies ignore fundamentals, I directly compare futures price reactions on World Agricultural Supply and Demand Estimates (WASDE) from the United States Department of Agriculture (USDA) with the publication of traders' positions from the COT report. Considering the "financialization" of commodity markets and the developments of commodity prices during the financial crisis 2007/08, the whole sample ranging from January 1996 to June 2014 is divided into two subsamples. Besides, price reactions are computed for various developments of fundamental news and traders' positions: for all, for positive and for negative developments, and for extremely positive and extremely negative developments separately.

The findings of the event study can be summarized as follows: fundamental news from the WASDE report remain an important source for pricing in grain futures markets. Nevertheless, a shift of importance from fundamental news to the publication of COT traders' positions is observed in corn and wheat futures markets. Furthermore, price reactions to the publications of traders' positions occur on the day of data collection of traders' positions. Traders imitating the position changes of large traders seem to anticipate the tendencies contained in the COT report.

The fifth study „Traders' Motivation and Hedging Pressure in Commodity Futures Markets" (co-authored by Kamal Smimou) aims to reveal the motives behind the position changes of different market participants. In addition, we examine how the interaction between the different traders affects prices in commodity futures markets. Several studies analyzing the motivations of traders focus on individual trader categories and subgroups of commodities. In contrast to these approaches, we examine all trader categories listed in the DCOT report according to their motivations to trade. Important aspects are past returns, hedging pressure, and proxies for the U.S. dollar exchange rate, the equity market, the bond market, and financial sentiment. The data sample we use for this approach includes all commodity markets with available DCOT reports: 22 commodities from each commodity-subgroup (energies, metals, and softs).

Moreover, the interaction between the different trader categories and the influence on commodity futures returns resulting from this interaction is examined in a second step. We take into account observed factors affecting the motivation of different trader categories when analyzing the interaction effects.

We find that speculators are driven by momentum trading and hedging pressure. Moreover, speculators are short-term oriented profit seekers who revise their positions frequently. Hedgers exhibit persistence in their trading behavior and they are contrarian traders. Among the financial factors, a U.S. dollar index captures a considerable share of traders' positions variability. The interaction analysis demonstrates that on average speculators and hedgers appear to be the most important traders influencing pricing in commodity markets.

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The Impact of Speculation on Precious Metals Futures Markets

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Abstract

Existing research finds little evidence that speculative activity in futures markets has any impact on precious metals' spot prices. We examine whether speculators' positions predict returns and return volatility in precious metals futures markets. We use two proxies for speculative activity: non-commercial traders and money managers. Money managers are a subcategory of non-commercial traders that is associated with professional speculators. Our analysis distinguishes between short- and long-term dynamics. Whereas we cannot confirm any short-term impact of speculators on returns and conditional volatility in the period after 2006, the weekly changes in non-commercial traders' positions appear to have a destabilizing impact on subsequent conditional volatility in gold, silver and palladium futures markets in the period prior to June 2006. Moreover, we cannot rule out a long-term, potentially destabilizing, impact on returns when accumulated positions of speculators over monthly horizons are considered.

***Keywords*:** Precious Metals Futures Markets, Speculation, Granger causality.

***JEL Classification*:** Q02, G12, G13, D84.

Price Discovery and Trading Activity in Commodity Futures Markets

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Abstract

We analyze whether and how the trading activity of different trader types impacts the contribution of the futures market to the price discovery process and the rate of convergence between spot and futures markets for a broad range of commodity futures markets over the 1999-2014 period. There is strong evidence that speculators (commodity index traders) increase (reduce) the rate of convergence between spot and futures markets. By contrast, there is only scarce evidence that trading activity of any trader category affects the contribution of the futures market to price discovery process that is computed based on the permanent-transitory decomposition of Gonzalo and Granger (1995).

Keywords: Price Discovery, Rate of Convergence, Speculators, Hedgers, Index Traders.

***JEL Classification*:** G13, G14, Q02.

1 Introduction

The price discovery process describes how fundamental information is incorporated into asset prices. If a commodity is traded in several markets, price discovery takes place in at least one of these markets. Prices in different markets share one or more common stochastic trends, while intermarket arbitrage prevents prices from drifting apart from the common trends. One of these stochastic common factors is the implicit efficient price, which is unobservable and reflects the fundamental value, whereas prices observed in individual markets additionally contain temporary effects such as inventory adjustments as well as bid and ask spreads (Baillie et al, 2002; Figuerola-Ferretti and Gonzalo, 2010). New information in one or several markets determines the efficient implicit price.

Traditionally, three strands of literature on price discovery in commodity spot and futures markets can be distinguished. The first approach analyzes temporal precedence based on the framework of Garbade and Silber (1983). Garbade and Silber (1983) develop a model of simultaneous price dynamics where current spot and futures prices are related to their lagged values. Based on this methodology, price discovery processes have been examined for crude oil, heating oil and gasoline (e.g. Schwarz and Szakmary, 1994), feeder cattle (e.g. Oellermann et al., 1989) and live hogs (e.g. Schroeder and Goodwin, 1991). The second strand of literature relies on the Granger causality framework and relates returns on spot (futures) markets to past returns on futures (spot) markets. For instance, Bekiros and Diks (2008) and Hernandez and Torero (2010) examine linear and non-linear causality between spot and futures returns for crude oil and agricultural commodities. Narayan et al. (2013) account for structural breaks and find strong evidence of predictability of spot by futures returns in crude oil, gold, silver and platinum markets. Lee and Zhang (2011) examine the relation between spot and futures crude oil markets based on a vector error correction model (VECM) that allows for a quantile-varying cointegrating vector and find that the causal relationship depends on the maturity of futures contracts and spot market performance. Wang and Wu (2013) extend the cointegration analysis by incorporating the idea that fixed adjustment and transaction costs impede a linear convergence towards a long-run equilibrium. Using a threshold VECM, they show that crude oil futures prices drive spot prices only for short-term horizons (weekly frequency), whereas for longer-term horizons (monthly and quarterly data) both spot and futures markets contribute to the formation of the long-run equilibrium. The third strand of literature implements the price discovery measures of Hasbrouck (1995) and Gonzalo and Granger (1995). As opposed to Hasbrouck (1995) who assumes that price volatility reflects information flows and assigns a higher information share to the market that contributes more to the total price variance, Gonzalo and Granger (1995) decompose the price discovery process into common and temporary factors and consider only the contributions of individual markets to the common factor in the price process. Ivanov (2013) explores the contribution of spot, futures and exchange-traded funds to the price discovery process of gold, silver and oil using intraday data at one minute interval from March 2009 to August 2009. Based on the Hasbrouck's (1995) information shares, Ivanov (2013) finds that exchange-traded funds dominate the price discovery for gold and silver, while futures prices are information-dominant in case of oil. Using the methodology of Gonzalo and Granger (1995), Figuerola-Ferretti and Gonzalo (2010) examine the contributions to the price discovery process of spot and futures markets for non-ferrous metals (aluminium, copper, lead, nickel and zinc). They find that the futures market dominates the spot market in terms of price discovery in most liquid commodity markets, whereas spot prices are more information-dominant in the least liquid lead market. In the equilibrium model of Figuerola-Ferretti and Gonzalo (2010), cointegration naturally arises in the presence of finite elasticity of supply of arbitrage services and endogenously modelled convenience yields. By contrast, Dolatabadi et al. (2015) use a fractionally cointegrated VAR analysis. They find more evidence in favor of the spot market leading the price discovery process than Figuerola-Ferretti and Gonzalo (2010): Price discovery takes exclusively place in the spot (futures) market for copper, lead and zinc (aluminum and nickel).

Our study is most closely related to the study of Chen et al. (2014), who investigate the impact of various trader positions from the CFTC report on price discovery in currency futures markets. Their measure of information efficiency is based on information shares of Hasbrouck (1995), Gonzalo and Granger (1995) and Lien and Shrestha (2009). They find that rising hedging (speculative) activity has a negative (positive) impact on the contribution of the futures market to price discovery. The decomposition of trading activity in its expected and unexpected components confirms these findings for the total trading activity in case of hedgers: Both expected and unexpected changes in net positions of hedgers lower the information share of the futures market.

We focus on the contribution of futures markets to the price discovery process based on the model of Garbade and Silber (1983) and the price discovery measure of Gonzalo and Granger (1995). Gonzalo and Granger (1995) decompose the price process into transitory and permanent components. Contributions of each market to the price discovery process are exclusively determined by the permanent component of the price discovery process. The derivation is based on adjustment parameters of the underlying vector error correction model. In this case, the price discovery process is assumed to be determined by a market's adjustment to deviations from the long-run equilibrium. An additional measure of market efficiency is the rate of convergence of spot and futures prices of Garbade and Silber (1983). It is inversely related to the elasticity of supply of arbitrage services. The lower the rate of convergence, the faster the prices in spot and futures markets converge.

Our major contribution to the existing research is not the identification of the role of futures markets in the price discovery process (which has been extensively examined in the empirical research), but the focus on the impact of trading activity in futures markets on the price discovery process. Hence, our research aim is closely related to the study of Chen et al. (2014), who explore the influence of speculators, hedgers and small traders on the contribution to the price discovery process of currency futures markets for EUR-USD and JPY-USD. To our knowledge, no comparable analysis has been conducted in the context of commodity futures markets. Whereas the impact of speculative and hedging activity on futures and spot returns and volatility in agricultural, energy and metal commodity markets has been extensively examined in the existing literature, the impact of different trader categories on the contribution of the futures market to price discovery has been so far neglected by the empirical research. We consider a broad range of commodities: agricultural, energy and precious metals markets. The analyzed commodities differ in several important aspects such as storage costs, durability, industrial profile and hedging potential. Moreover, various proxies for trading activity are considered: open interest, index traders and trader categories from the Commitments of Traders (COT) and Disaggregated Commitments of Traders (DCOT) reports of the Commodity Futures Trading Commission (CFTC).

Our major hypotheses are as follows. The trading activity of speculators who are commonly assumed to provide liquidity to hedgers may "correct" the mispricing induced by hedging pressure as suggested by the backwardation theory of Hirshleifer

(1990). Indeed, rational arbitrageurs are supposed to recognize market inefficiencies, alleviate noise-driven price movements and restore prices back to their fundamental values (De Long et al., 1990). This idea has been confirmed for currency markets by Chen et al. (2014). In the theoretical model of Goldstein and Yang (2015), private information of financial traders increases the contribution of the futures market to the price discovery process not only because of risk sharing, but also as a consequence of private information about demand shocks. In this case, we expect a positive effect of speculative activity on the contribution of the futures market to the price discovery process and on the speed of convergence between spot and futures markets.

However, whether speculators always perform the role of liquidity providers for hedgers is arguable. In the model of Goldstein and Yang (2015), the spot price is determined by supply and demand shocks. Solely risk-averse hedgers are informed about supply shocks. Demand shocks are partially known to risk-averse financial traders who receive diverse private signals. Whether the financial traders provide or demand liquidity depends on their information: If financial traders are well informed about demand shocks, hedgers provide liquidity to speculators, while in case of volatile supply shocks financial traders provide liquidity to hedgers. Recent research reveals that hedgers may also provide short-term liquidity to speculators who engage in momentum trading (e.g. Sanders et al., 2004; Cheng and Xiong, 2014; Kang et al., 2014): Momentum trading is not related to private information. It cannot be excluded that some speculators act as irrational noise traders who overreact to new information (Chen et al., 2014). In this case, the speculative activity would contribute little to price discovery: On the contrary, noise traders would lead futures prices further apart from fundamental values. Therefore, the contribution of the futures market to the price discovery process would decrease. Similarly, the activity of uniformed speculators in futures markets would have a detrimental effect on the speed of convergence between spot and futures markets.

A competitive and liquid market is an important prerequisite for the price discovery process. Given that price discovery depends on how new information is incorporated into commodity prices, futures market liquidity is assumed to affect the contribution of the futures market to the price discovery process and market efficiency. For instance, Figuerola-Ferretti and Gonzalo (2010) document that the futures market plays a more decisive role in the price discovery process in more liquid metal markets such as aluminium and copper, whereas the contribution of the futures market to the price discovery process is substantially lower in the less liquid lead market. Similarly, Garbade and Silber (1983) confirm the importance of liquidity of the futures market for the price discovery process for agricultural commodities. Similar results can be observed for Canadian and Brazilian agricultural commodities (Brockman and Tse, 1995; Mattos and Garcia, 2004). However, the more recent evidence of Adämmer et al. (2015) suggests that efficient price discovery takes even place in thinly traded futures markets. In general, open interest as a proxy for market liquidity, is supposed to be positively related to the contribution of the futures market to the price discovery process and should increase the speed of convergence. Our cross-sectional analysis would capture not only the time-series changes in market liquidity in an individual commodity market, but also the liquidity differences across a wide range of 16 commodity markets. However, if a minimum threshold of trading activity is already sufficient for the efficient price discovery in the futures market, as suggested by Adämmer et al. (2015), we may not find any effect of market liquidity on the contribution of the futures market to the price discovery. Similar reasoning applies to the speed of convergence between spot and futures markets.

Our study is structured as follows. Data and methodology are summarized in Section 2. Section 3 presents the empirical results. Section 4 concludes.

2 Data and Methodology

2.1 Data

Our estimation period ranges from January 1, 1999 to December 31, 2014. Table 1 shows the spot and futures markets that are used for our analysis. All spot and futures prices (denominated in USD) are collected from Datastream with the exception of WTI crude oil, for which the spot price is collected from the website of the International Energy Agency (IEA).

Futures contracts are chosen on the basis of size and global importance. The CFTC disclosure of trader positions is also an important selection criterion. Spot markets are chosen such that the time delay between futures and spot price determination is minimized. For energy commodities and grains, the time delay between spot and futures markets is negligible as all spot markets are located close to the corresponding futures markets. Regarding soft commodities, only for sugar, the location of the spot and futures market differs in time zones: The time delay between Sao Paulo and New York amounts to one hour. Since we rely on daily data, the time discrepancy of one hour is not supposed to distort the empirical results.

However, the problem related to the time discrepancy between spot and futures markets is more severe for precious metals. While the London Bullion Market is the most important spot market for gold and silver, the New York Commodity Exchange (COMEX) is the relevant futures market. To overcome the time difference between London and New York, spot prices of the less (economically) important Handy & Harman spot market are used. Handy & Harman is located in New York and the spot prices are also used in the empirical research on the relationship between spot and futures markets (e.g. Garbade and Silber, 1983; Narayan et al., 2013). The spot prices for platinum and palladium are obtained from the afternoon fixing of the London Platinum & Palladium Market (LPPM). The afternoon fixing begins in London 2:00 p.m. local time, the NYMEX settlement starts at 12:58 -1:00 p.m. for palladium and 1:03-1:05 p.m. for platinum, both in local time. With a time delay of five hours between London and New York, the time difference between the two prices amounts to a maximum of four hours, depending on how long the fixing process lasts. Thus, when the afternoon fixing begins at 9:00 a.m. New York time, the spot prices are already known at the settlement time at the NYMEX. Hence, a downward bias for the importance of the spot market for price discovery arises since the futures price provides “fresher” information. However, the contributions to the price discovery process for platinum and palladium show a high variation in their yearly values.[1] This speaks against an extreme bias induced by the time delay, which would be expected to produce a constantly dominating futures price in the price discovery process throughout the examined time period. Another reason, which reduces the scope of the time delay problem, is that we are not interested in the absolute values per se, but in the relative link between the efficiency of the futures market (relative to the spot market) and trader positions.

In order to derive contributions of spot and futures markets to price discovery, we create continuous spot and futures price series. For the calculation of futures returns, we adopt the following rolling procedure: In order to ensure that only the most liquid futures contracts are used, the switching to the second-nearby contract takes place when

[1] The results on the yearly PD shares are available on demand.

its open interest exceeds that of the first-nearby contract. Based on the derived daily returns R_t, we construct continuous spot and futures price series P_t as $P_t = P_{t-1} * (1 + R_t)$ with the start value $P_0 = 100$ as of January 1, 1999. The logarithms of spot and future prices, p_t, are used in the analysis of price discovery based on the procedure of Gonzalo and Granger (1995). For the derivation of the rates of convergence, the actual spot and futures prices are used (denominated in the USD).

Positions

The data on trader positions is collected from COT and DCOT reports of the CFTC. Each Tuesday, the CFTC collects the data and publishes it on Friday. The COT report divides all traders into three categories: commercials, non-commercials and non-reportables. Commercials use futures markets for hedging purposes, while non-commercials are typically associated with speculation. Non-reportable traders do not reach the reporting level, which is determined by the CFTC. They are small traders who engage in either commercial or non-commercial business. On average 70 to 90 percent of all open positions are reportable positions.[2] In our sample, the small traders' share of total open interest ranges from 6.7 to 25.2 percent (Table 2). The DCOT report provides a more detailed classification of commercial and non-commercial traders into four categories: producers/merchants/processors/users, swap dealers, money managers and other reportables.[3]

2.2 Methodology

Price Discovery

We use two measures for the efficiency of the price discovery process: the rate of convergence between spot and futures prices as well as the contribution of the futures markets to the price discovery process of Gonzalo and Granger (1995).

Gonzalo and Granger (1995) assume that the difference-stationary price process p_t can be decomposed into a transitory component $\widetilde{p_t}$ and a permanent component $A_1 f_t$:

$$p_t = A_1 f_t + \widetilde{p_t} \qquad (1).$$

[2] See: http://www.cftc.gov/MarketReports/CommitmentsofTraders/ExplanatoryNotes/index.htm

[3] A detailed description of different trader categories of the DCOT report is available in Section 3.3.

Both the transitory and permanent components can be represented as linear combinations of the initial process p_t. Whereas shocks to the transitory component are not considered to be relevant to the price discovery process, it is the permanent component that is assumed to play the decisive role in the price discovery process and determines contributions to the price discovery of different markets (Figuerola-Ferretti and Gonzalo, 2010). The permanent component is defined as the product of the $(k \times 1)$-vector f_t of k common factors and the loading matrix A_1. Based on the assumption that only shocks to the permanent component $A_1 f_t$ affect the long-run forecast of p_t, the common factor f_t can be derived as a linear combination of p_t:

$$f_t = \alpha'_{\perp} p_t \qquad (2),$$

where $\alpha_{\perp}$ measures each market's contribution to the common factor. It is the (2×1)-vector that is orthogonal to the vector of adjustment parameters $\alpha' = (\alpha_1, \alpha_2)$ in the following vector error correction model (VECM):

$$\Delta p_t = \alpha\beta' p_{t-1} + \sum_{i=1}^{n} \Gamma_i \Delta p_{t-i} + e_t \text{ with } e_t \sim (0, \Omega),\ \Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \qquad (3).$$

In our bivariate model with spot and futures prices $p_t = \binom{p_1}{p_2}$, $\alpha_{\perp}$ is computed as

$$\alpha'_{\perp} = \left(\frac{\alpha_2}{-\alpha_1+\alpha_2}, \frac{-\alpha_1}{-\alpha_1+\alpha_2}\right) \qquad (4).$$

The terms $\frac{\alpha_2}{-\alpha_1+\alpha_2}$ and $\frac{-\alpha_1}{-\alpha_1+\alpha_2}$ measure the contributions of markets one and two, i.e. spot and futures markets, respectively, to the common factor that represents the price discovery process (Baillie et al., 2002; Figuerola-Ferretti and Gonzalo, 2010). Relying on the vector of adjustment parameters means that only the markets' adjustments to the deviations from the long-run equilibrium are relevant for price discovery. The market that adjusts least is assumed to play a minor role in the price discovery process (Baillie et al., 2002).

Cabrera et al. (2009) argue that one of the drawbacks of the permanent-transitory (PT) decomposition of Gonzalo and Granger (1995) as shown in Eq. (4) is that the factor weights $\frac{\alpha_2}{-\alpha_1+\alpha_2}$ and $\frac{-\alpha_1}{-\alpha_1+\alpha_2}$ may take negative values. Interpreting negative factor weights in terms of contributions to the price discovery process is problematic. Therefore, Cabrera et al. (2009) argue that it is not the sign, but the relative magnitude of the factor weights that reflects the price discovery process. Their procedure for the calculation of the vector of factor weights $\widetilde{\alpha_\perp}$ is as follows:

$$\widetilde{\alpha_\perp} = (abs(A_1^{*\prime}) * \iota)^{-1} abs(A_1^*) \qquad (5),$$

where the matrix A_1^* is the matrix that is orthogonal to the matrix of adjustment parameters in the vector error correction model and ι is the $(n \times 1)$ vector of ones (Cabrera et al., 2009).

In our bivariate model, Eq. (4) simplifies to:

$$\widetilde{\alpha_\perp} = \left[abs(\alpha_\perp')\binom{1}{1}\right]^{-1} abs(\alpha_\perp) \qquad (6).$$

A disadvantage of the permanent-transitory decomposition of Gonzalo and Granger (2002) is that the matrix of price innovations is not taken into account while computing the markets' contributions to the price discovery process (Baillie et al., 2002). Another frequently used measure to capture contributions to price discovery of different markets is the information share of Hasbrouck (1995). Hasbrouck (1995) assumes that the implicit efficient price of a security traded in multiple markets is common to all markets and its variations can be traced back to different markets. Using a vector moving average representation, Hasbrouck (1995) decomposes the price vector p_t into a non-stochastic vector of initial values, a transitory zero-mean covariance stationary process and the random walk component that is common to all prices. The price discovery process is defined in terms of innovations to the common factor term or, more precisely, as the variance of innovations to this common random walk component. Information share is the contribution of the market to the total efficient price innovation variance. The underlying assumption is that price volatility reflects information flows. Hence, a higher information share is assigned to the market that contributes more to the total price variance. Baillie et al. (2002) show that the permanent-transitory decomposition of the price process of Gonzalo and Granger (1995) and the information share of Hasbrouck (1995) may yield comparable results only in the absence of a contemporaneous correlation between the disturbances in the individual markets: While the PT measure of Gonzalo and Granger (1995) depends solely on the vector of adjustment parameters, the

IS measure of Hasbrouck (1995) depends on the correlation between the two prices (Baillie et al., 2002).

We rely on the model of Figuerola-Ferretti and Gonzalo (2010) who show that departing from the standard cointegration vector (1,-1) allows accounting for long-run backwardation or contango. This is especially important for commodity markets. We do not use the information share of Hasbrouck (1995) for two reasons: Firstly, as argued by Figuerola-Ferretti and Gonzalo (2010), there is no straightforward procedure to eliminate the contemporaneous correlations of the error terms from the vector moving average representation for the calculation of the information shares of Hasbrouck (1995). Hasbrouck (1995) deals with this issue by calculating upper and lower bounds for his information share. The modified measure of Lien and Shrestha (2009) overcomes the problem of the two bounds of the traditional information share of Hasbrouck (1995). However, the information share of Hasbrouck (1995) and its modified version of Lien and Shrestha can only be used in situations where the spot and futures price series are cointegrated with a one-to-one cointegrating relationship. For commodity markets that are characterized by switches from contango to backwardation and vice versa, the assumption of a constant cointegrating vector is not fulfilled. The model of Figuerola-Ferretti and Gonzalo (2010) allows departing from the standard cointegration vector (1, -1) and therefore accounts for long-run backwardation or contango.[4] Although this procedure does not explicitly account for switches between backwardation and contango market regimes, it at least captures the idea of long-run backwardation and contango. We derive our price discovery measures on an annual basis and, thus, at least partially alleviate the problem related to the switches between backwardation/contango regimes.

We compute the measures for the contribution to the price discovery process of spot and futures markets as specified by Eq. (4) based on the vector error correction model (Eq. (3)). Since the cointegration between spot and futures price series is an underlying assumption of the vector error correction model, as a first step, the Johansen test is used to test whether cointegration between spot and futures prices exists during the entire time span from 1999 to 2014. In this case, the Johansen trace and/or maximum eigenvalue tests indicate one cointegrationg relationship (at least 20 percent

[4] Lien and Shrestha (2014) modify the information share to allow deviations from one-to-one cointegrating vector and the results are consistent with the information shares derived based on the permanent-transitory decomposition of Gonzalo and Granger (1995). Their generalized information share is particularly suitable for an analysis of interrelated, not necessarily almost identical markets (Lien & Shrestha, 2014).

significance level) for CBOT and Minneapolis wheat, soybeans, oats, gold, corn, cotton and natural gas.[5] For these commodity markets, the contributions of spot and futures markets to the price discovery process are computed for every individual year of the 1999-2014 sample period based on Eq. (6). For the remaining commodities, the cointegration is tested on an annual basis and, only if the Johansen test detects cointegration at (at least) 20 percent significance level, the contributions of spot and futures markets to the price discovery process are calculated.

Rate of convergence

To measure the rate of convergence between spot and futures prices, we use the model of Garbade and Silber (1983):

$$basis_t = \alpha + \delta basis_{t-1} + e_t \tag{7},$$

which is an AR (1)-model with $basis_t = futures\ price_t - spot\ price_t$ (Garbade and Silber, 1983; Moosa et al., 2002; Zhang and Wang, 2013). According to Garbade and Silber (1983), δ is inversely related to the elasticity of supply of arbitrage services. Thus, the lower (higher) the value of δ, the faster (slower) the rate of convergence and therefore the greater (lower) the elasticity to substitute the futures by spot market positions. Hence, it can be also interpreted as a measure to evaluate the risk transfer function for hedgers. If spot and futures prices do not converge until the expiration of a contract, hedgers may suffer from the price discrepancy between spot and futures price at expiration of a futures contract and the price risk of their physical holdings would not be optimally offset. Since lower values of δ are associated with quicker convergence, we define the measure as inverse rate of convergence (IC).

As we are interested in the relationship between the rate of convergence and the trading activity in terms of a cross-sectional analysis, we focus on the last 20 trading days until expiration of a contract in order to ensure the comparability for 16 different commodity markets. The number of contracts within a year varies largely among commodities. While for all energy futures contracts, contracts for each month are available, most grains futures (e.g. wheat and corn) have only five contracts per year. The longer the period until expiration, the more the IC measure may be distorted: For some com-

[5] The optimal lag order has been determined based on the Akaike criterion. Depending on the commodity markets, we augment Eq. (2) by different trend specifications (if required).

modities such as the three energy commodities, several contracts would approach the expiration at the same time, whereas for other commodities such as grains only one contract is near expiration.

Fama/Mc Beth (1973) cross-sectional regressions

The focus of our analysis is the impact of different trader categories on the price discovery in the futures market and the convergence between spot and futures markets. Three different measures for the trading activity are considered: the share of long and short positions in the total open interest, i.e. the *share* variable, the *pressure* variable (i.e. the price pressure that is defined as the net long (short) positions relative to the total interest for speculators and small traders (hedgers)) and the propensity to trade, i.e. the PY variable, that is defined as the sum of the absolute differences from period t to $t-1$ scaled by the total positions in period t and $t-1$:

Share of Speculators:[6]

$$Spec_t = \frac{long\ positions_t + short\ positions_t + spreading\ positions_t}{2 * total\ open\ interest_t} \quad (8).$$

Share of Traders:

$$Share_t^k = \frac{long\ positions_t + short\ positions_t}{2 * total\ open\ interest_t} \quad (9).$$

Trading Pressure:

$$Trading\ Pre_t^l = \frac{long\ positions_t - short\ positions_t}{total\ open\ interest_t} \quad (10).$$

Hedging Pressure:

$$HP_t = \frac{short\ positions_t - long\ positions_t}{total\ open\ interest_t} \quad (11).$$

[6] In the COT report, spreading positions are only reported for non-commercial traders. Those are the number of positions long and short in different maturities, namely calendar spread positions.

Propensity to trade:[7]

$$PY_t = \frac{abs(long\ positions_t - long\ positions_{t-1}) + abs(short\ positions_t - short\ positions_{t-1})}{long\ positions_{t-1} + short\ positions_{t-1}} \quad (12),$$

with $k = hedgers,\ small\ traders$ and $l = speculators, small\ traders$. The relative importance of a trading group (i.e. the *share* variable) is supposed to reflect the influence of the magnitude of the total positions of traders, both long and short positions, relative to the market. By contrast, the variable *pressure* reflects the net long or short positions of traders relative to the total market (i.e. open interest). As opposed to the market share of a particular trader group, the trading pressure captures whether the trader group is net long or net short, i.e. whether it is associated with buying or selling pressure. The *propensity to trade* describes how actively the traders adjust their positions (Kang et al., 2014). The positive correlation between trading pressure and propensity to trade may indicate a positive relationship between net positions and their changes.

The cross-sectional analysis of the impact of traders on the measures for price discovery (PD) and for the inverse of the rate of convergence (IC) is based on the Fama and Mc Beth (1973) procedure:

$$PD_{i,t} = \alpha + \beta^{PD} TM_{i,t}^{j} + e_t \quad (13a).$$

$$IC_{i,t} = \alpha + \beta^{IC} TM_{i,t}^{j} + e_t \quad (13b),$$

with $PD_{i,t}$ for the measure of the contribution of the futures market to price discovery in t for commodity i (computed based on Eq. (4) and (6)), and $IC_{i,t}$ as the measure for the inverse of the rate of convergence in t for commodity i (calculated based on Eq. (7)). $TM_{i,t}^{j}$ represents the different trading measures in t and commodity market i. For each year from January 1999 to December 2014 the PD and IC values are calculated. Then, both are regressed cross-sectionally over the $i = \{1, \dots, 16\}$ commodity futures markets on the yearly averages of the j trading measures for the three trader categories. The results of the yearly cross-sectional regressions can be found in Table A.1 – A.8. The long-term relationship of the PD and IC values with trading measures is calculated

[7] PY_t is calculated for each trader category in this way. All the j trading measures are yearly averages of weekly data on trader positions.

according to Fama and McBeth (1973) as the average of the yearly values for β^{PD} and β^{IC}. T-statistics of the coefficients β^{PD} and β^{RC} are calculated as:

$$\frac{\overline{\beta^m}}{\sigma_{\beta^m} / \sqrt{n}} \qquad (14),$$

where σ_{β^m} is the standard deviation of the yearly coefficients β^{PD} and β^{IC} and n the number of yearly cross-sectional regressions. Additionally, the averages of the t-values from the yearly cross-sectional regressions are reported.

3 Results

3.1 Price Discovery and Trading Activity: Descriptive Statistics

Price Discovery Process

Table 2 shows the averages of the different measures that are used to measure the price discovery process: the contribution to the price discovery process of the futures markets PD (Panel A) and the convergence measure IC that is inversely related to the speed of convergence between spot and futures markets (Panel B).

The higher the PD values the greater is the contribution of the futures market to the price discovery process relative to the spot market. A value of one would mean that the futures market alone determines the price discovery process, whereas a value of zero would indicate that price discovery takes place entirely in the spot market. A PD measure of 0.5 would reflect that both markets contribute equally to the price discovery process of a commodity. Panel A in Table 2 shows that the contributions of the futures market to the price discovery process, averaged over the 1999-2014 period, take only intermediate values: They range from 0.426 for Minneapolis wheat to 0.762 for silver. In general, the futures market plays a leading role in the price discovery process: PD measures above 0.5 are observed in 13 out of 16 commodity markets. The leading role of the futures market in the price discovery process may be explained by the fact that futures markets capture new information in a more efficient way than spot markets due to higher liquidity and transparency and lower transaction costs. The leading role of the futures market for heating oil and natural gas is consistent with the evidence of Shrestha (2014). Only in case of Minneapolis wheat, corn and crude oil, the spot market dominates the futures market in the price discovery process. The results for the CBOT corn market are at variance with the evidence of Kuiper et al. (2002) who confirm a leading role of the futures market. However, the difference may be due to the different sample periods. The differences among the three energy markets (heating oil, crude oil and natural gas) deserve some discussion: The spot markets for heating oil and natural gas are more or less localized markets. However, the international status of the crude oil spot market is characterized by a participation of large informed oil companies and refineries (Shrestha, 2014).

The highest contribution of the futures market to the price discovery process can be observed for the four precious metals (Table A.1). This is not surprising given that the used gold and silver spot markets (Handy & Harman Base) are economically less important. Furthermore, time delays exist in the price fixing between spot and futures markets in case of platinum and palladium. There is a high variation in the PD measures among the agricultural commodities: In case of Kansas wheat, oats and cocoa, the futures market clearly dominates the price discovery process. For CBOT wheat, soybeans and cotton, the contribution of the futures market to the price discovery process is only marginally higher than that of the spot market.

The convergence measure (IC) in Panel B of Table 2 reflects how quickly spot and futures prices converge during the 20-days-period preceding the expiration date of the futures contract. Importantly, the IC measure is inversely related to the speed of convergence: Low values of the IC measure indicate a high convergence between the spot and futures prices. For instance, a value of one would imply that spot and futures prices do not converge at all. The closer the IC measure is to the value of zero, the faster spot and futures prices converge towards expiration of the contract. Precious metals are the commodity group that is characterized not only by the highest contribution of the futures market to the price discovery process, but also by lowest IC values (Table A.1). While metals are on average the fastest to converge, the grains markets display the highest IC measures and, thus, converge rather slowly. Softs are also typically characterized by high IC measures: Sugar has the highest value (IC=0.943), which indicates a very low rate of convergence between spot and futures prices. The three energy commodities account for intermediate values of the both measures for price discovery/ convergence (Table A.1).

Although there is no clear-cut theoretical link between the contribution of the futures market to the price discovery according to the permanent-transitory decomposition of Gonzalo and Granger (1995) and the rate of convergence of Garbade and Silber (1983), the relationship between both variables is generally negative. Markets with the highest contributions of the futures market to the price discovery (gold, silver, platinum and palladium) are also those characterized by the lowest IC measures, i.e. the highest speed of convergence. Commodities with comparatively low contributions of the futures market to the price discovery (e.g. wheat, MW, corn, sugar) are among those with the highest IC measures, i.e. lowest rates of convergence. A notable exception is the Kansas wheat where both the contribution of the futures market to the price discovery and the IC measure are among the highest.

Trading activity

Panels C-F of Table 2 summarizes the descriptive statistics for the different measures of trading activity. For speculators, the average share of the total open interest is around 26 percent. Exceptionally, the relative importance of speculators for Minneapolis wheat, oats and heating oil futures markets is substantially lower. Hedgers' share ranges between 50 and 60 percent, whereas long and short positions of small traders account on average for 15 percent of the total open interest. The low values of the relative importance of speculators in Minneapolis wheat and oats futures markets seem to be compensated by small traders who are strongly represented in these two grains markets with 25.2 and 23.1 percent of the total open interest, respectively. Only precious metals futures markets are characterized by a pronounced price pressure coming from net long/ short positions of speculators/hedgers. Net long positions of small traders are on average around zero. In the precious metals and oats futures markets, net long positions amount to 10 percent of open interest.

The propensity to trade is on average the highest for speculators, indicating that they trade more "impatiently" compared to hedgers and small traders. Trading activity of hedgers is characterized by the lowest values for the propensity to trade measure, which can be explained by the fact that hedgers do not regularly revise their positions as they are mainly interested in hedging their physical commodity exposure over intermediate time horizons. This is usually done at low frequencies instead of frequent revisions of positions, as it is typical for speculators. Open interest is a common proxy for market depth. The largest markets by number of open contracts are crude oil, corn, natural gas, sugar and soybean futures markets (Panel F, Table 2).

As far as the relationship between different measures for trading activity is concerned, Table A.2 shows that the used measures for trading activity are not interchangeable. Only for hedgers, there is a strong positive link between net short positions scaled by open interest and the propensity to trade. Net positions scaled by open interest (i.e. "buying" or "selling" pressure) and the propensities to trade are positively correlated, whereas the relationship between the relative importance of a trading group in the total trading activity (i.e. the share variable) and the propensity to trade is negative for all three trader groups. The positive correlation between the trading pressure and propensity to trade may indicate a positive relationship between net positions and their changes.

Recent studies point out that a high correlation between hedgers and speculators may make it difficult to distinguish between the price effects of the two trader groups (e.g. Bosch and Pradkhan, 2015). Table A.3 shows the correlations between different trader groups (speculators, hedgers and small traders) for different proxies for trading activity (i.e. the share, pressure and propensity to trade variables) computed for 16 commodity markets based on the 1999-2014 averages. Whereas the correlations between the propensities to trade of different trader categories are comparatively moderate, the correlation between the relative importance of speculators and hedgers amounts to -0.64. The problem is especially severe in case of the net trader positions (i.e. trading pressure) of speculators and hedgers as well as hedgers and small traders. In these cases the correlations amount to 0.95 and 0.74, respectively. In addition, Table A.4 shows the correlations between the different measures for trading activity in individual commodity markets. A consideration of individual commodity markets also supports the idea that trading activities of the examined trader groups (speculators, hedgers, small traders) are highly correlated. As opposed to Table A.3, Table A.4 shows that propensities to trade of different trader categories are highly correlated in most commodity markets. Given the high correlations between the trading activities of different trader categories, it would be difficult to discern which trader category influences the price discovery. For instance, a significant coefficient estimate on the net short positions of hedgers in the Fama-MacBeth regressions may be the consequence of a significant impact of net long positions of speculators, given that the correlation between net long positions of speculators and net long positions of hedgers is close to one.

3.2 Interaction between Price Discovery and Trading Activity (COT report)

Table 3 summarizes the results for the Fama-MacBeth estimations where the contribution of the futures market to the price discovery process is regressed on various measures of trading activity. There is no evidence that either trader category impacts the contribution of the futures market to the price discovery. However, Table A.6 shows that speculative and hedging pressure is positively related to price discovery, yet exclusively at the level of individual years (2006, 2008, 2012, 2014). Interestingly, the net long positions of small traders also seem to increase the leading role of the futures market in the price discovery process for the years 2006 and 2008 (Table A.6). However, given the high correlation between speculative and hedging pressure, as shown in Table A.3 and A.4, it is not possible to deduce which trader category (either speculators or hedgers or small traders) enhances the price discovery process. It is possible that not an individual trader category, but the interaction of all trader types that has a positive effect on the role of the futures market in the price discovery process. Furthermore, Table A.7 reveals that the propensity to trade of hedgers had a strong positive effect on price discovery during the 2008/09 financial crisis. In this period, commodity prices experienced extreme conditions with prices moving from a long-term high to a long-term low for most commodities. During this period, hedgers were forced to frequently revise their positions in order to keep the physical holdings hedged in an environment of extreme price swings. As hedgers provide additional liquidity supply in extreme market conditions, the commodity futures market could have profited from a more active participation of hedgers. Consequently, this improves price discovery in futures markets.[8]

The absence of any significant impact of traders' positions on the contribution of the futures market to the price discovery process in commodity futures markets is at variance with the evidence of Chen et al. (2014) for currency futures markets. Chen et al. (2014) find that the speculative/hedging activity is positively/negatively related to contribution of the currency futures markets to the price discovery that is measured by

[8] Importantly, the estimation results for individual years should not be given much emphasis: The number of observations for estimations at the level of individual years is 14 at maximum, often even lower: PD shares are calculated only for those commodities where spot and futures prices are cointegrated.

the information share of Hasbrouck (1995). We do not use the information share of Hasbrouck (1995) that may not be suitable in case of commodity markets that frequently switch between contango/backwardation regimes. The information share of Hasbrouck (1995) and the information share computed based on the permanent-transitory decomposition of Gonzalo and Granger (1995) should yield identical results only under the assumption that there is no contemporaneous correlation between the disturbances in the individual markets (Baillie et al., 2002). Moreover, our estimations are carried out on an annual basis, whereas Chen et al. (2014) use high frequency data to derive the information shares and carry out the estimations on a weekly basis. The use of high frequency data allows incorporating the time-varying component of the price discovery process that may be better matched with weekly changes in trader positions. Relying on annual data also allows capturing the time-varying component of price discovery, but to a lesser extent.

The size of the futures market measured by open interest seems completely unrelated to price discovery (Table 3). With the exception at the level of individual years, the coefficient estimate on open interest is significant (Table A.8). However, the negative effect of open interest on the contribution of the futures market to price discovery in years 2008 and 2009 is not compatible with our initial hypothesis that a higher market depth facilitates market efficiency and price discovery in the futures markets.

Table 4 summarizes the cross-sectional results for the rate of convergence. As opposed to the permanent-transitory measure, there is more evidence that trading activity impacts the rate of convergence. For speculators, there is the strongest evidence that their trading activity (either the relative importance or net long positions) increases the speed of convergence between spot and futures markets. Hedging pressure also increases the rate of convergence, but this effect is only marginally significant. The trading activity of small traders does not appear to impact the rate of convergence. This may not be surprising given that the economic significance of this trader category is substantially lower than that of hedgers and speculators. An additional reason why non-reportable traders may not play an important role in the price discovery process may be that this trader category is comprised of heterogeneous traders with different preferences and trading strategies. In this case, the effect of the trading activity of non-reportable traders as a group may be rather insignificant as opposed to hedgers and speculators who represent more homogeneous trader groups.

Considering the individual years (Tables A.9-A.10) confirms the estimation results on the aggregate basis. In addition, we detect a significant negative effect of net long positions of small (i.e. non-reportable) traders during the 2004-2012 period. However, due to high correlations between the three trader categories (Table A.3), the negative coefficient estimate on the IC measure cannot be interpreted as evidence that small traders increase the convergence between spot and futures markets.

At the level of individual years[9] (Table A.9), hedgers and small traders have a positive effect on the IC measure, i.e. a higher share of small traders is associated with a slower rate of convergence during the 1999-2001 period, whereas a higher share of traders reduces the rate of convergence during the 2006-2008 period. Remarkably, hedgers' propensity to trade has an opposite effect on the convergence between spot and futures markets during the 2006-2008 period (Table A.11). Hence, just having more hedgers in a market is no guarantee for futures contracts to converge, actively trading hedgers are needed for a quicker convergence at least in some years. Similar results, but much weaker, are found for small traders. For the open interest, there is no significant impact on the rate of convergence even at the level of individual years (Table A.12). This finding indirectly supports the importance of the interaction between the traders: Market size measured by open interest plays a minor role for the pricing behavior of a futures market regarding price discovery and rate of convergence. There are even cases (in year 2000, 2008, and 2009) where a higher open interest leads to a deterioration of price discovery in futures markets. Extreme market conditions, at least for 2008 and 2009, could be a further reason. The larger the futures market, the more likely it is that a larger amount of unprofessional traders participate in the futures market. For small investors it is much more common to invest in large futures markets (e.g. energy commodities as well as gold and silver) or grains (e.g. corn, soybeans and CBOT wheat). While active hedgers contribute positively to price discovery, unprofessional small investors could be the market's share that hinder price discovery by passive investing. Thus, a higher contribution to price discovery is left over for spot markets, where small investors do not participate.

[9] The results for individual years should be treated with caution: The number of observations for estimations at the level of individual years is 14.

3.3 Disaggregated Commitments of Traders Report and Index Investment Data

The fact that the used proxies for hedgers and speculators, i.e. the commercial and non-commercial traders of the COT report, are highly aggregated across different trader types may counteract our purpose to find out which trader category is associated with informational trades and, thus, enhances the efficiency of the futures market. For instance, professional speculators such as hedge funds are more likely to benefit from private information on fundamentals than the smaller less informed speculators, e.g. other reportables. However, the non-commercial category of the COT report aggregates both trader categories. Similarly, the commercial trader category of the COT report encompasses both the producers/merchants/processors/users (PMPUs) and the swap dealers. PMPUs represent the typical hedgers who hedge their physical commodity exposures. Swap dealers often act as counterparties to the commodity index investors who have no physical commodity exposure. Consequently, they are less likely to gather information on commodity fundamentals. Whereas commodity index investment is typically associated with non-informational trading, producers/merchants/processors/ users may benefit from private information on fundamentals. To account for the differences within the commercial and non-commercial trader category, we also consider the subgroups of these trader categories as provided by the DCOT report.

The DCOT report disaggregates the commercial and non-commercial traders into producers/merchants/processors/users, swap dealers, money managers and other reportables. PMPUs, a subgroup of the commercial trader category of the COT report, are involved in "the production, processing, packing or handling of a physical commodity" and enter futures markets in order to hedge the associated risks (CFTC, 2009). Swap dealers that are classified as commercial traders in the COT report use futures markets to hedge risks related to their dealing in swaps for a commodity (CFTC, 2009). According to CFTC (2009), the swap dealers' counterparties are typically speculative traders and traditional PMPUs. The non-commercial trader category is decomposed into money managers and other reportables. The money managers (or managed money) category encompass registered commodity trading advisors, registered commodity pool operators and unregistered funds that are engaged in managing and conducting organized futures trading on behalf of clients (CFTC, 2009). Although this trader category is commonly associated with professional speculators such as hedge funds, which try to gather information on commodity fundamentals and trade on the discovered (private) information, several studies identify trend following as one of the main investment strategies of commodity trading advisors (Baltas and Kosowski, 2013; Hutchinson and O'Brian, 2014). Trend following is at variance with the idea that trading activity of professional speculators carries private information and, thus, enhances contribution to price discovery of the futures market and convergence between spot and futures markets. Other reportables represent "a wide array of other non-commercial (speculative) traders" (CFTC, 2009).

In addition, we also account for commodity index investors. Due to the immense growth of index investment in the last decade, the CFTC has reacted to the need for transparency and supplies data on index traders' positions on a quarterly basis going back to December 2007. From June 30, 2010 onwards, they provide monthly data. All investors engaged in index trading activities, such as index funds, swap dealers, pension funds, hedge funds, mutual funds, exchange traded funds or other exchange traded products, are required to report their positions to the CFTC. The study of the U.S. Senate Permanent Subcommittee on Investigations (USS PSoI, 2009) documents that the activity of index investors leads to a divergence between spot and futures prices and that spot and futures prices do not converge near expiration anymore in the wheat futures markets. As index traders are typically associated with passive long investment and driven by motives such as portfolio diversification, they can be seen as uninformed traders: They invest in broad commodity indices (e.g. the Standard & Poor's-Goldman Sachs Commodity Index and the Dow Jones-UBS Commodity Index or sub-indices) and usually do not analyze individual commodities in detail. By contrast, Stoll and Whaley (2010) do not find any link between the lack of convergence and commodity index investment: They demonstrate that despite the fact, that convergence of the wheat futures contract has actually worsened, it can still be effectively used as a tool to manage risk in commodity business. Although commodity index traders are commonly associated with noise traders (USS PSoI, 2009), Brunetti and Reiffen (2014) argue that commodity index investors provide price risk insurance to hedgers and, thus, reduce the cost of hedging. In this respect, the trading activity of commodity index investors would fulfill the role of traditional speculators.

Tables 5-7 summarize the results on the impact of the individual trader categories on the contribution of the futures market to price discovery and the inverse rate of convergence. The following trader categories are considered: money managers and other reportables, producers/merchants/processors/users (PMPUs) and swap dealers, non-reportables as well as commodity index traders. The decomposition of commercial and non-commercial traders in subcategories (money managers and other reportables, PMPUs and swap dealers) adds little to the previous results as shown in Table 3: There is no evidence that any trader category impacts the contribution of the futures market to the price discovery process (Table 5, Panel A in Table 7). When the individual years are considered, the coefficient estimates on the share variable are only marginally significant for money managers and PMPUs for individual years. For the trading pressure variable, there is some evidence that positions of money managers and non-reportables increase the contribution of the futures market to price discovery at the level of individual years. This would be consistent with the idea that professional speculators trade on private information and correct any potential mispricing (Table A.13). For the propensity to trade of swap dealers, there is only controversial evidence at the level of individual years: If significant, the sign of the propensity to trade variable changes sign across individual years (Panel C, Table A.13). For commodity index traders, there is solely controversial evidence on the price discovery process: The relative importance and the rising net long positions of index traders, i.e. the share and pressure variables, reduce the price efficiency of the futures market, whereas their propensity to trade is positively related to the futures market efficiency (Table A.15). These results are especially puzzling given that they can be observed for the same year 2014. Theoretically, a higher volatility of positions, i.e. a frequent adjustment of positions, of commodity index traders that are typically associated with non-information trading may bring additional noise and should reduce the contribution of the futures market to the price discovery process. The observed positive coefficient estimate on the index traders' propensity to trade is not consistent with this idea.

As opposed to the lack of statistical significance regarding the contribution of the futures market to price discovery, statistically significant results are obtained for the inverse measure of convergence (Table 6; Panel B, Table 7). For money managers, there is strong evidence that the relative importance and rising net long positions reduce the inverse rate of convergence, i.e. that they increase the convergence between spot and futures markets. The positive effect on convergence would be consistent with the idea that professional speculators trade on private information on commodity fundamentals and, thus, increase the efficiency of commodity futures markets (Panel B, Table 6). In addition, we observe a negative relationship between rising net long positions of other reportables and the inverse rate of convergence (Panel D, Table 6). These results are compatible with results on professional speculators (money managers). In this respect, the results on the decomposition of non-commercial traders into professional speculators (money managers) and other speculative traders (other reportables) are consistent with the results on non-commercial traders (Table 4): Different types of speculators are associated with a higher rate of convergence between spot and futures markets, which would speak in favor of the informational content of the trading activity of all types of speculators. These appear to correct mispricing and increase the convergence between spot and futures markets.

Strikingly, we observe an opposite effect for hedgers: The relative importance of the PMPUs, i.e. the share variable, is positively related to the inverse rate of convergence, i.e. the PMPUs appear to deter the convergence between spot and futures markets (Panel A, Table 6). Similar results can be achieved for another subcategory of the commercial traders, the swap dealers: Their positions, i.e. the trading pressure variable, have a negative effect on the rate of convergence (Panel C, Table 6). Hence, both subcategories of the "commercial trader" category appear to reduce the rate of convergence between spot and futures markets. This evidence is not consistent with the prediction that trading activity of hedgers is driven by private information. The results on the PMPUs and swap dealers are also not compatible with the results on the "commercial trader" category before it has been decomposed in its subcategories: Panel B in Table 4 shows that the hedging pressure variable is negatively related to the inverse rate of convergence, i.e. that rising short positions of hedgers increase the convergence between spot and futures markets. Although the positive sign on the share variable in Panel B in Table 4 is statistically not significant, it is consistent with the results on the PMPUs as shown in Panel A in Table 6.

The relative importance of commodity index traders (i.e. the share variable) and their trading activity (i.e. the trading pressure variable) increase the inverse rate of convergence (Panel B, Table 7). This evidence is consistent with the idea that the rising participation of commodity index traders whose trading activity is typically related to diversification. Additionally, it is not supposed to reflect fundamental information, which may impede the convergence between spot and futures markets.

It is worth pointing out that our results may be contaminated by endogeneity concerns. From our regression specifications that relate measures of price discovery over the period t to the trading activity over the same period, we cannot infer with precision whether a significant coefficient estimate on the trading activity variable reflects the impact of trading activity on price discovery or the impact of price discovery (i.e. the efficiency of futures markets) on trader participation in futures markets.[10] However, our adopted interpretation in terms of an impact of traders on price discovery is more intuitive. Omitted variable bias may also impair the validity of causal evidence: Empirical research suggests that there exist important linkages and spillovers (Silvennoinen and Thorp, 2013; Mensi et al., 2013; Gao and Liu, 2014). If the activity of the examined trader groups is correlated with macroeconomic or financial variables, the significant coefficient estimate on trading activity may simply reflect the impact of these omitted variables on the price discovery process.

4 Conclusion

We analyze the price discovery process in a broad range of commodity futures markets (agricultural, energy and precious metals markets) over the 1999-2014 period. Following Chen et al. (2014) who investigate the impact of various trader positions from the CFTC report on price discovery in currency futures markets, we explore how the trading activity of different trader types (hedgers, speculators, index traders) impacts the contribution of the futures market to price discovery and the rate of convergence between commodity spot and futures markets.

There is only scarce evidence that any trader category affects the contribution of the futures market to the price discovery process when the total sample period is considered. Statistically significant effects are only detected at the level of individual years. In this case, there is some evidence that commercial and non-commercial traders en-

[10] For instance, a positive relationship between the rate of convergence and speculative activity may be interpreted as evidence of the informational content of the trading activity of speculators who correct mispricing and increase convergence between spot and futures markets. At the same time, an alternative interpretation of a positive relationship between the rate of convergence and speculative activity cannot be ruled out: If markets are highly inefficient, speculators may be less likely to enter futures markets, as predicted by the model of De Long et al. (1990) who show that risk-averse arbitrageurs are less likely to enter markets and engage in arbitrage in the presence of noise since they are in danger to incur losses when they liquidate their investments in mispriced assets. Similarly, a negative relationship between hedging activity and the rate of convergence between spot and futures markets may be interpreted either as an indication that hedging activity contains noise and reduces market efficiency or as an indication that producers are less likely to hedge via futures markets if spot and futures markets do not converge.

hance the price discovery process in futures markets. However, given the high correlation between speculative and hedging pressure, we cannot identify which trader category is responsible for this effect. A possible explanation may be that it is the interaction of both trader types that has a positive effect on the contribution of the futures market to the price discovery process. When the decomposition of non-commercial traders in subcategories is considered, there is some evidence that positions of money managers and non-reportables increase the contribution of the futures market to price discovery at the level of individual years. This result would be consistent with the idea that professional speculators trade on private information and correct any potential mispricing. Yet, this evidence is only marginally significant. For commodity index traders whose activity is frequently associated with noise, there is only controversial evidence: The relative importance and the rising net long positions of index traders reduce the contribution of the futures market to the price discovery process. By contrast, their propensity to trade is positively related to the futures market efficiency.

There is strong evidence that the relative importance and rising net long positions of money managers and rising net long positions of other reportables increase the rate of convergence between spot and futures markets. These results are consistent with the idea of the informational content of trading activity of all types of speculators. They correct mispricing and increase convergence between spot and futures markets. By contrast, we obtain only controversial results for hedgers. Producers/merchants/processors/users and swap dealers, i.e. the two subcategories of the commercial trader category, reduce the rate of convergence between spot and futures markets. This evidence is at variance with the prediction that trading activity of hedgers is driven by private information. On the other hand, rising short positions of commercial traders appear to increase the convergence between spot and futures markets. The relative importance of commodity index traders and their trading activity are negatively related to the rate of convergence between spot and futures markets. This is consistent with the allegation that a rising participation of commodity index traders, whose trading activity is typically related to diversification and is not supposed to reflect fundamental information, may impede the convergence between spot and futures markets.

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Appendix

A Tables

Table 1: Futures and Spot Price Data

Futures Prices	*Corresponding Spot Prices*
Energy	
WTI Light Crude Oil (NYMEX) - CL	WTI Crude FOB Oil Spot Cushing (IEA)
Natural Gas (NYMEX) - NG	Natural Gas Henry Hub
NY Harbor Heating Oil (NYMEX) - HO	Heating Oil No. 2 FOB New York Harbor
Metals	
Gold (COMEX) - GC	Gold, Handy & Harman Base
Silver (COMEX) - SL	Silver, Handy & Harman Base
Platinum (NYMEX) - PL	Platinum, LPPM (afternoon fixing)
Palladium (NYMEX) - PA	Palladium, LPPM (afternoon fixing)
Grains	
Corn (CBOT) - C	Corn, No. 2 Yellow (USDA)
Soybeans (CBOT) - S	Soybeans, No. 1 Yellow (USDA)
Wheat (CBOT) - W	Soft Red Winter Index, MGEX
Wheat (KCBOT) - KW	Hard Red Winter Wheat, Kansas City Terminal
Wheat (MGEX) - MW	Hard Red Spring Wheat, Minneapolis Terminal
Oats (CBOT) - O	Oats, No. 2 Milling Minneapolis
Softs	
Cocoa (ICE)[11] - CC	Cocoa-ICCO
Cotton No. 2 (ICE)[2] - CT	Cotton, 1 1/16 Strict Low -Middling, Memphis
Sugar No. 11 (ICE)[2] - SB	Sugar, Crystal, Sao Paulo[12]

Note: Table 1 lists all futures contracts used in the analysis with their corresponding futures markets, abbreviations and spot prices. NYMEX – New York Mercantile Exchange, COMEX – New York Commodity Exchange, CBOT – Chicago Board of Trade, KCBOT – Kansas City Board of Trade, MGEX – Minneapolis Grain Exchange, ICE – Intercontinental Exchange, WTI – West Texas Intermediate, FOB – free on board, EIA –International Energy Agency, USDA – United States Department of Agriculture, LPPM – London Platinum and Palladium Market, ICCO - International Cocoa Organization.

[11] Since September 2007 ICE, former NYBOT.
[12] Largest sugar producer Brazil and only one hour delay to NY.

Table 2: Descriptive Statistics, averages of all measures

	W	KW	MW	C	S	O	CT	CC	SB	CL	HO	NAT	GC	SI	PL	PA
	Panel A: price discovery (PD)															
PD measure	0.545	0.709	0.426	0.472	0.524	0.596	0.506	0.644	0.571	0.455	0.713	0.557	0.633	0.762	0.702	0.636
	Panel B: inverse rate of convergence (IC)															
ME measure	0.912	0.725	0.792	0.831	0.748	0.843	0.866	0.628	0.943	0.519	0.692	0.594	0.083	0.119	0.269	0.245
	Panel C: Speculation measures															
Share	0.307	0.228	0.151	0.246	0.260	0.186	0.272	0.246	0.210	0.233	0.170	0.292	0.330	0.312	0.352	0.324
Pressure	-0.015	0.127	0.092	0.103	0.121	0.166	0.044	0.078	0.098	0.059	0.038	-0.076	0.225	0.249	0.435	0.329
PY	0.069	0.092	0.138	0.073	0.086	0.127	0.098	0.085	0.097	0.077	0.126	0.087	0.087	0.084	0.104	0.091
	Panel D: Hedger measures															
Share	0.478	0.538	0.573	0.508	0.494	0.567	0.588	0.648	0.624	0.594	0.628	0.499	0.495	0.452	0.504	0.547
Pressure	-0.022	0.112	0.109	0.030	0.098	0.307	0.083	0.115	0.144	0.061	0.088	-0.028	0.313	0.404	0.534	0.391
PY	0.043	0.043	0.051	0.033	0.043	0.062	0.050	0.032	0.040	0.031	0.041	0.031	0.058	0.058	0.071	0.059
	Panel E: Small Trader measures															
Share	0.149	0.195	0.252	0.190	0.181	0.231	0.106	0.067	0.131	0.076	0.150	0.081	0.121	0.175	0.139	0.121
Pressure	-0.007	-0.015	0.016	-0.073	-0.022	0.141	0.040	0.037	0.046	0.002	0.050	0.048	0.088	0.155	0.099	0.062
PY	0.053	0.070	0.087	0.032	0.046	0.094	0.082	0.116	0.077	0.085	0.063	0.066	0.080	0.059	0.100	0.113
	Panel F: Open Interest[1]															
Open Interest	2.925	1.112	0.392	9.031	3.827	0.119	1.349	1.347	4.986	10.372	2.219	7.032	3.281	1.104	0.234	0.152

Note: Table 2 reports the arithmetic averages of the yearly values of the price discovery measure and the inverse rate of convergence (Panel A & B), and the arithmetic averages of the trading measures (Panel C – F) based on weekly data. All averages are calculated for the time period January 1, 1999 to December 31, 2014. W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, C=Corn, S=Soybeans, O=Oats, CT=Cotton, CC=Cocoa, SB=Sugar, CL= WTI Crude Oil, HO=Heating Oil, NG=Natural Gas, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium. PY= propensity to trade. [1]- number of open interest divided by 100.000.

Table 3: Cross-sectional results of several trading activity (COT) measures on price discovery

	Coeff.	t-stat (FM)	Avg. t.stat	max	min	Avg. Adj. R^2
	Panel A: Speculators					
Share	0.514	0.35	0.18	2.065	-1.379	-0.02
Speculative Pressure	0.210	0.50	0.69	0.938	-0.461	0.05
Prospensity to trade	-0.144	-0.06	0.15	4.283	-5.436	-0.03
	Panel B: Hedgers					
Share	0.151	0.16	0.17	1.698	-1.466	0.01
Hedging Pressure	0.242	0.80	0.97	0.844	-0.318	0.07
Prospensity to trade	3.285	0.42	0.46	26.406	-5.709	0.04
	Panel C: Small Trader					
Share	-0.328	0.42	0.46	1.900	-2.210	0.01
Speculative Pressure	0.877	1.34	1.05	1.904	-0.567	0.04
Prospensity to trade	0.889	0.43	0.48	5.218	-3.024	-0.01
	Panel D: Open Interest					
Open Interest	-0.013	0.60	-0.77	0.064	-0.086	0.06

Note: Table 3 reports the coefficients, the t-statistic according Fama-McBeth (FM, 1973), the arithmetic average of the t-statistics from the yearly cross-sectional results, the maximum and the minimum of all yearly calculated coefficients, and the arithmetic average of the yearly adjusted R^2 from the cross-sectional regression.

Table 4: Cross-sectional results of several trading activity (COT) measures on inverse of convergence

	Coeff.	t-stat (FM)	Avg. t.stat	max	min	Avg. Adj. R^2
	Panel A: Speculators					
Share	-1.921**	-2.55	-2.05	-0.701	-3.246	0.18
Speculative Pressure	-0.889**	-2.43	-2.22	0.040	-1.519	0.21
Prospensity to trade	0.552	0.17	0.37	4.526	-6.258	0.00
	Panel B: Hedgers					
Share	0.876	0.92	0.96	2.849	-0.437	0.04
Hedging Pressure	-0.746*	-2.05	-2.49	0.048	-1.274	0.26
Prospensity to trade	-7.219	-1.43	-1.37	2.018	-15.920	0.08
	Panel C: Small Trader					
Share	1.214	1.73	0.93	2.360	0.310	0.01
Speculative Pressure	-1.931	-1.46	-1.83	0.278	-4.102	0.16
Prospensity to trade	-2.937	-1.16	-0.94	1.084	-8.875	0.01
	Panel D: Open Interest					
Open Interest	0.005	0.22	0.44	0.027	-0.048	-0.02

Note: Table 4 reports the coefficients, the t-statistic according Fama-McBeth (FM, 1973), the arithmetic average of the t-statistics from the yearly cross-sectional results, the maximum and the minimum of all yearly calculated coefficients, and the arithmetic average of the yearly adjusted R^2 from the cross-sectional regression. **, * denote significance at 5 and 10 percent level, respectively.

Table 5: Cross-sectional results of several trading activity (DCOT) measures on price discovery

	Coeff.	t-stat (FM)	Avg. t.stat	max	min	Avg. Adj. R^2
	Panel A: PMPU					
Share	-0.010	-0.02	-0.14	0.852	-0.981	-0.01
Hedging Pressure	0.172	0.32	0.27	1.093	-0.460	0.02
Prospensity to trade	0.925	0.15	0.19	12.704	-6.218	-0.01
	Panel B: Managed Money					
Share	0.056	0.06	0.23	1.540	-1.551	-0.02
Speculative Pressure	0.295	0.44	0.81	1.288	-0.607	0.14
Prospensity to trade	1.078	0.75	0.45	3.857	-1.107	-0.04
	Panel C: Swap Dealer					
Share	0.531	0.56	0.48	1.443	-1.100	-0.01
Speculative Pressure	-0.306	-0.65	-1.24	0.431	-0.893	0.12
Prospensity to trade	1.860	0.60	0.69	6.073	-2.852	0.20
	Panel D: Other Reportables					
Share	0.507	0.26	0.16	3.709	-2.053	-0.06
Speculative Pressure	0.970	0.55	0.73	3.109	-2.191	0.09
Prospensity to trade	-0.231	-0.22	-0.24	0.719	-2.626	-0.05
	Panel C: Non Reportables					
Share	-0.037	-0.03	-0.16	1.897	-1.847	-0.02
Speculative Pressure	0.295	0.44	0.81	1.288	-0.607	0.14
Prospensity to trade	1.719	0.82	0.91	5.157	-0.745	0.04

Note: Table 5 reports the coefficients, the t-statistic according Fama-McBeth (FM, 1973), the arithmetic average of the t-statistics from the yearly cross-sectional results, the maximum and the minimum of all yearly calculated coefficients, and the arithmetic average of the yearly adjusted R^2 from the cross-sectional regression.

Table 6: Cross-sectional results of several trading activity (DCOT) measures on inverse of convergence

	Coeff.	t-stat (FM)	Avg. t.stat	max	min	Avg. Adj. R^2
	Panel A: PMPU					
Share	0.93**	2.16	1.30	1.49	0.21	0.06
Hedging Pressure	-0.46	-1.10	-0.76	0.11	-1.08	0.00
Prospensity to trade	-1.58	-0.18	-0.47	10.51	-12.14	0.05
	Panel B: Managed Money					
Share	-2.31***	-3.00	-2.18	-1.41	-3.47	0.20
Speculative Pressure	-1.31***	-5.91	-2.68	-1.12	-1.78	0.29
Prospensity to trade	0.63	0.23	0.37	2.76	-4.90	0.00
	Panel C: Swap Dealer					
Share	-1.07	-0.73	-0.86	0.86	-3.19	0.02
Speculative Pressure	1.38***	8.46	3.75	1.55	1.08	0.43
Prospensity to trade	-4.71	-1.24	-1.74	-0.23	-10.29	0.13
	Panel D: Other Reportables					
Share	-2.71	-1.25	-0.87	1.73	-5.22	0.01
Speculative Pressure	-2.61***	-3.61	-1.65	-1.25	-3.28	0.11
Prospensity to trade	0.34	0.35	0.19	1.87	-1.29	-0.06
	Panel E: Non Reportables					
Share	1.06*	1.79	0.63	2.28	0.39	-0.04
Speculative Pressure	-2.94***	-3.96	-2.47	-2.06	-4.02	0.25
Prospensity to trade	-4.31*	-1.68	-1.19	-0.89	-8.77	0.04

Note: Table 6 reports the coefficients, the t-statistic according Fama-McBeth (FM, 1973), the arithmetic average of the t-statistics from the yearly cross-sectional results, the maximum and the minimum of all yearly calculated coefficients, and the arithmetic average of the yearly adjusted R^2 from the cross-sectional regression. ***, **, * denote significance at 1, 5 and 10 percent level, respectively.

Table 7: Cross-sectional results of several trading activity (Index Investment) measures on price discovery and inverse of convergence

	Coeff.	t-stat (FM)	Avg. t.stat	max	min	Avg. Adj. R^2
Panel A: Price Discovery						
Share	-0.342	-0.59	-1.30	0.645	-1.023	0.19
Speculative Pressure	-0.728	-0.60	-0.93	1.451	-1.930	0.12
Prospensity to trade	4.136	1.02	1.18	8.356	-1.858	0.16
Panel B: Inverse of Convergence						
Share	0.735***	3.32	3.32	2.010	1.028	0.37
Speculative Pressure	1.400*	1.79	1.66	2.067	-0.071	0.18
Prospensity to trade	-6.548	-0.83	-1.34	3.167	-18.740	0.17

Note: Table 7 reports the coefficients, the t-statistic according Fama-McBeth (FM, 1973), the arithmetic average of the t-statistics from the yearly cross-sectional results, the maximum and the minimum of all yearly calculated coefficients, and the arithmetic average of the yearly adjusted R^2 from the cross-sectional regression. ***, * denote significance at 1 and 10 percent level, respectively.

Table A.1: Averages for price discovery and inverse of convergence measures

	Average contribution of the futures market to the price discovery process	***Average inverse rate of convergence***
Agriculture	0.555	0.810
Energy	0.575	0.602
Precious Metals	0.683	0.179

Note: Table A.1 shows the average PD and IC shares for different commodity groups.

Table A.2: Correlations between different measures for trading activity

	Speculators	***Hedgers***	***Small traders***
Share & Pressure	0.47	-0.23	-0.01
Share & PY	-0.62	-0.33	-0.31
Pressure & PY	0.11	0.87	0.46

Note: Table A.2 reports the correlations the correlations between different measures of trading activity for speculators (COT non-commercial traders), hedgers (COT commercial traders) and small traders (COT non-reportable traders): the share variable (Eq. (9)-(11)), the pressure variable (Eq. (12)-(14)) and the propensity to trade (Eq. (15)).

Table A.3: Correlations between different trader categories (1999-2014 cross-section)

	Share	***Pressure***	***PY***
Speculators & Hedgers	-0.64	0.95	0.40
Speculators & Small Traders	-0.45	0.48	0.33
Hedgers & Small Traders	-0.24	0.74	0.36

Note: Table A.3 reports the correlations between different traders categories computed based on the 1999-2014 cross-section.

Table A.4: Correlations between different trader categories for individual commodities

	WHC	WHK	WHM	COR	SOY	OAT	COT	COC	SUG	CRU	HEA	NAT	GOL	SIL	PLA	PAL
Panel A: Share Variable																
Speculators & Hedgers	-0.577	-0.908	-0.771	-0.473	0.239	-0.363	-0.725	-0.928	-0.768	-0.980	-0.851	-0.979	-0.575	-0.778	-0.742	-0.922
Speculators & Small Traders	-0.551	-0.769	-0.505	-0.819	-0.808	-0.030	-0.547	-0.547	-0.686	-0.861	-0.747	-0.562	-0.578	0.254	-0.752	-0.741
Hedgers & Small Traders	0.879	-0.005	-0.268	-0.722	-0.320	0.507	-0.489	-0.417	-0.274	-0.352	0.339	0.561	-0.483	0.636	-0.401	-0.642
Panel B: Trading Pressure Variable																
Speculators & Hedgers	0.724	0.788	0.933	0.945	0.777	0.678	0.993	0.971	0.878	0.990	0.840	0.978	0.971	0.959	0.968	0.965
Speculators & Small Traders	0.241	-0.504	-0.822	-0.013	-0.219	-0.264	0.042	-0.243	-0.192	0.556	0.129	0.239	0.292	0.726	0.185	0.611
Hedgers & Small Traders	0.844	0.134	-0.561	0.315	0.444	0.530	0.163	-0.003	0.301	0.666	0.647	0.435	0.511	0.890	0.427	0.798
Panel C: Propensity to Trade																
Speculators & Hedgers	0.896	0.799	0.859	0.905	0.858	0.633	0.831	0.724	0.936	0.836	0.568	0.701	0.866	0.742	0.790	-0.124
Speculators & Small Traders	0.324	0.556	0.659	0.158	0.151	0.032	-0.102	0.604	0.453	0.111	0.717	0.694	0.509	-0.041	0.662	0.533
Hedgers & Small Traders	0.146	0.614	0.595	-0.005	0.142	-0.186	-0.021	0.623	0.467	0.295	0.611	0.348	0.608	0.359	0.357	0.268

Note: Table A.4 reports the correlations between trading activity of different trader groups computed based on annual values for each of 16 commodity markets.

Table A.5: Yearly cross-sectional results of traders' share (COT) on price discovery

	Spec	t-stat	Adj. R^2	Hedge	t-stat	Adj. R^2	NR	t-stat	Adj. R^2
1999	0.147	0.13	-0.12	1.698	1.80	0.20	-2.210**	-2.41	0.35
2000	0.157	0.22	-0.11	-0.050	-0.10	-0.11	0.127	0.15	-0.11
2001	-1.379*	-1.91	0.19	0.885	1.70	0.15	-1.302	-1.14	0.03
2002	-0.620	-0.62	-0.05	0.350	0.49	-0.06	0.075	0.07	-0.08
2003	0.122	0.08	-0.11	0.979	0.85	-0.03	-1.436	-1.32	0.07
2004	0.451	0.48	-0.08	-1.466	-1.44	0.09	0.759	0.74	-0.04
2005	2.065**	2.40	0.28	-1.166	-1.25	0.04	-1.838	-1.71	0.14
2006	0.319	0.38	-0.06	-0.200	-0.31	-0.06	0.875	1.06	0.01
2007	0.541	0.60	-0.05	-1.320	-1.67	0.11	-1.001	-0.90	-0.01
2008	1.224*	1.84	0.17	-0.346	-0.41	-0.07	-0.671	-0.57	-0.06
2009	-1.289	-1.06	0.01	1.488	1.47	0.09	1.180	0.63	-0.06
2010	0.250	0.31	-0.08	0.307	0.44	-0.07	-0.390	-0.38	-0.08
2011	0.746	0.88	-0.02	-0.621	-0.80	-0.03	-1.841	-1.70	0.15
2012	0.030	0.03	-0.09	0.289	0.30	-0.08	1.900	1.40	0.08
2013	-0.645	-0.62	-0.07	0.950	0.83	-0.03	0.881	0.59	-0.07
2014	0.031	0.05	-0.11	0.644	0.90	-0.02	-0.360	-0.35	-0.10

Note: Table A.5 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of COT traders' share on the price discovery measure. **, * denote significance at 5 and 10 percent level, respectively.

Table A.6: Yearly cross-sectional results of trading pressure (COT) on price discovery

	Spec pressure	t-stat	Adj. R^2	HP	t-stat	Adj. R^2	NR pressure	t-stat	Adj. R^2
1999	0.472	0.97	-0.01	0.418	1.13	0.03	0.795	0.85	-0.03
2000	-0.240	-0.51	-0.08	0.260	0.75	-0.05	1.072**	2.30	0.30
2001	0.321	0.39	-0.08	0.037	0.06	-0.10	-0.567	-0.47	0.65
2002	0.210	0.46	-0.06	0.219	0.79	-0.03	0.675	1.14	0.02
2003	-0.461	-0.69	-0.06	-0.050	-0.11	-0.11	0.946	0.88	-0.02
2004	0.178	0.52	-0.07	0.193	0.84	-0.03	0.621	1.18	0.03
2005	0.217	0.51	-0.07	0.118	0.38	-0.08	0.035	0.04	-0.09
2006	0.684**	2.76	0.31	0.508**	2.89	0.33	1.134**	2.15	0.19
2007	-0.426	-1.24	0.04	-0.214	-0.77	-0.03	0.382	0.47	-0.06
2008	0.696*	2.16	0.23	0.635**	2.62	0.33	1.837**	2.30	0.26
2009	0.287	0.51	-0.07	0.286	0.62	-0.06	0.944	0.62	-0.06
2010	0.370	1.75	0.15	0.331*	1.87	0.17	0.787	1.17	0.03
2011	-0.440	-1.66	0.14	-0.318	-1.30	0.06	0.408	0.40	-0.08
2012	0.938**	2.58	0.32	0.844**	2.72	0.35	1.761	1.28	0.05
2013	0.081	0.19	-0.11	0.129	0.33	-0.10	1.904	0.90	-0.02
2014	0.477**	2.29	0.30	0.471**	2.69	0.38	1.293	1.63	0.14

Note: Table A.6 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of COT trading pressure on the price discovery measure. **, * denote significance at 5 and 10 percent level, respectively.

Table A.7: Yearly cross-sectional results of traders‘propensity to trade on price discovery

	PY Spec	t-stat	Adj. R^2	PY hedge	t-stat	Adj. R^2	PY NR	t-stat	Adj. R^2
1999	-1.806	-1.45	0.11	-1.424	-0.45	-0.10	2.300	0.66	-0.07
2000	-0.578	-0.56	-0.07	0.169	0.05	-0.11	0.296	0.22	-0.11
2001	1.214	0.69	-0.05	-4.580*	-1.94	0.20	-0.911	-0.41	-0.08
2002	1.702	1.20	0.03	3.060	0.67	-0.04	0.855	0.52	-0.06
2003	-5.436	-1.58	0.13	-5.703	-1.21	0.04	1.194	0.47	-0.08
2004	0.318	0.22	-0.09	3.257	1.20	0.04	-3.024	-1.01	0.00
2005	-2.598	-1.29	0.05	-0.505	-0.12	-0.09	-1.760	-0.57	-0.06
2006	-3.629	-1.38	0.06	2.694	1.00	0.00	0.892	0.36	-0.06
2007	-1.847	3.17	-0.05	-1.889	-0.47	-0.06	-0.631	-0.26	-0.07
2008	1.228	0.35	-0.08	10.447**	2.98	0.40	2.261	1.51	0.10
2009	4.283	1.34	0.07	26.406**	2.50	0.32	1.008	0.27	-0.09
2010	-0.590	-0.22	-0.09	3.787	0.62	-0.05	4.274**	3.00	0.40
2011	0.363	0.09	-0.10	-3.612	-0.67	-0.05	0.242	0.08	-0.10
2012	0.998	0.43	-0.07	8.507	1.54	0.10	1.932	0.70	-0.04
2013	1.468	0.52	-0.08	2.020	0.25	-0.10	0.088	0.02	-0.11
2014	2.606	0.82	-0.03	9.924	1.50	0.11	5.218*	2.06	0.24

Note: Table A.7 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of COT traders' propensity to trade on the price discovery measure. **, * denote significance at 5 and 10 percent level, respectively.

Table A.8: Yearly cross-sectional results of open interest on price discovery

	OI	t-stat	Adj. R^2
1999	-0.006	-0.09	-0.12
2000	-0.086**	-2.80	0.41
2001	0.064	1.18	0.03
2002	-0.048	-1.07	0.01
2003	0.038	0.57	-0.07
2004	-0.028	-0.80	-0.03
2005	0.008	0.19	-0.09
2006	-0.017	-1.31	0.05
2007	0.013	1.03	0.00
2008	-0.033**	-3.10	0.42
2009	-0.060*	-1.95	0.20
2010	-0.014	-1.25	0.05
2011	0.015	1.06	0.01
2012	-0.023	-1.79	0.15
2013	-0.019	-0.98	0.00
2014	-0.010	-1.13	-0.03

Note: Table A.8 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of open interest on the price discovery measure. **, * denote significance at 5 and 10 percent level, respectively.

Table A.9: Yearly cross-sectional results of traders' share (COT) on inverse of convergence

	Spec	t-stat	Adj. R^2	Hedge	t-stat	Adj. R^2	NR	t-stat	Adj. R^2
1999	-1.007	-1.02	0.00	-0.210	-0.24	-0.07	2.360*	2.12	0.19
2000	-1.277	-1.71	0.11	0.036	0.06	-0.07	2.261**	2.23	0.21
2001	-1.252	-1.61	0.10	0.070	0.12	-0.07	2.186*	1.91	0.15
2002	-0.701	-0.55	-0.05	-0.217	-0.24	-0.07	1.139	0.88	-0.02
2003	-1.708	-1.41	0.06	0.383	0.36	-0.06	1.250	1.04	0.01
2004	-1.760	-1.50	0.08	0.689	0.70	-0.04	0.472	0.37	-0.06
2005	-2.030	-2.59	0.28	1.046	1.24	0.03	1.040	1.01	0.00
2006	-3.208***	-3.73	0.46	1.841**	2.29	0.22	0.310	0.25	-0.07
2007	-3.246***	-3.45	0.42	2.849***	3.00	0.35	0.955	0.65	-0.04
2008	-2.522***	-3.66	0.45	2.343***	3.16	0.37	0.755	0.51	-0.05
2009	-1.542	-1.72	0.12	0.701	0.82	-0.02	0.527	0.37	-0.06
2010	-2.648**	-2.60	0.28	1.124	1.11	0.01	1.209	0.68	-0.04
2011	-1.879	-1.58	0.09	0.807	0.71	-0.03	0.394	0.22	-0.07
2012	-1.833*	-1.97	0.16	1.712	1.61	0.10	0.975	0.53	-0.05
2013	-2.678**	-2.43	0.25	1.283	0.93	-0.01	2.281	1.35	0.05
2014	-1.454	-1.21	0.03	-0.437	-0.32	-0.06	1.319	0.74	-0.03

Note: Table A.9 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of COT traders' share on the inverse of convergence. ***, **, * denote significance at 1, 5 and 10 percent level, respectively.

Table A.10: Yearly cross-sectional results of trader's pressure (COT) on inverse of convergence

	Spec pressure	t-stat	Adj. R^2	HP	t-stat	Adj. R^2	NR pressure	t-stat	Adj. R^2
1999	-0.481	-1.03	0.00	-0.379	-1.07	0.01	-0.721	-0.74	-0.03
2000	0.040	0.06	-0.07	0.048	0.10	-0.07	0.076	0.09	-0.07
2001	-0.906	-0.99	0.00	-0.346	-0.53	-0.05	0.278	0.24	-0.07
2002	-0.523	-0.91	-0.01	-0.250	-0.70	-0.04	-0.256	-0.32	-0.06
2003	-0.589	-1.10	0.01	-0.542	-1.41	0.06	-1.733	-1.66	0.10
2004	-1.519***	-4.94	0.61	-0.950***	-4.16	0.52	-1.455*	-2.09	0.18
2005	-0.825**	-2.52	0.26	-0.591**	-2.49	0.26	-1.371*	-1.84	0.14
2006	-0.902**	-2.40	0.24	-0.756***	-3.01	0.35	-2.139***	-3.19	0.38
2007	-1.003**	-2.32	0.23	-0.995***	-3.38	0.41	-2.961***	-3.87	0.48
2008	-1.147**	-2.50	0.26	-1.005**	-2.85	0.32	-2.034*	-1.85	0.14
2009	-1.141***	-3.86	0.48	-1.012***	-4.65	0.58	-2.718***	-3.07	0.36
2010	-1.048***	-3.32	0.40	-1.022***	-4.37	0.55	-3.119***	-3.38	0.41
2011	-0.852*	-2.07	0.18	-0.854**	-2.42	0.25	-2.591*	-1.78	0.13
2012	-1.232**	-2.57	0.27	-1.274***	-3.35	0.41	-3.965**	-2.76	0.31
2013	-0.975*	-2.12	0.19	-0.962**	-2.34	0.23	-4.102	-1.75	0.12
2014	-1.117**	-2.92	0.33	-1.044***	-3.12	0.37	-2.086	-1.32	0.05

Note: Table A.10 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of COT trading pressure on the inverse of convergence. ***, **, * denote significance at 1, 5 and 10 percent level, respectively.

Table A.11: Yearly cross-sectional results of traders' propensity to trade on inverse of convergence

	PY Spec	t-stat	Adj. R^2	PY hedge	t-stat	Adj. R^2	PY NR	t-stat	Adj. R^2
1999	0.528	0.36	-0.06	-2.724	-0.95	-0.01	-0.847	-0.40	-0.06
2000	2.338	1.74	0.12	-5.956	-1.28	0.04	-1.480	-0.75	-0.03
2001	-0.529	-0.37	-0.06	-7.319***	-3.04	0.35	-4.095*	-1.81	0.13
2002	-2.162	-1.08	0.01	-8.801	-1.61	0.10	-3.279	-1.68	0.11
2003	4.526*	2.02	0.17	2.018	0.40	-0.06	-0.701	-0.26	-0.07
2004	0.995	0.50	-0.05	-2.788	-0.70	-0.03	1.084	0.34	-0.06
2005	2.094	1.14	0.02	-3.060	-0.88	-0.01	-0.450	-0.16	-0.07
2006	2.956	0.74	-0.03	-6.742*	-1.86	0.14	-2.325	-0.66	-0.04
2007	-5.679	-1.37	0.06	-13.918**	-3.20	0.38	-3.527	-1.07	0.01
2008	2.020	0.50	-0.05	-13.091**	-2.41	0.24	-1.050	-0.50	-0.05
2009	2.125	0.77	-0.03	-4.054	-0.42	-0.06	-2.830	-1.21	0.03
2010	3.021	0.80	-0.02	-9.956	-0.93	-0.01	-6.769***	-2.36	0.23
2011	-6.258	-1.16	0.02	-12.007	-1.72	0.12	-4.443	-0.97	0.00
2012	2.708	0.93	-0.01	-9.827	-1.36	0.05	-2.340	-0.65	-0.04
2013	3.419	1.01	0.00	-1.358	-0.17	-0.07	-5.066	-1.19	0.03
2014	-3.262	-0.55	-0.05	-15.920	-1.75	0.12	-8.875	-1.66	0.11

Note: Table A.11 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of COT traders' propensity to trade on the inverse of convergence. ***, **, * denote significance at 1, 5 and 10 percent level, respectively.

Table A.12: Yearly cross-sectional results of open interest on inverse of convergence

	OI	t-stat	Adj. R^2
1999	-0.048	-0.97	0.00
2000	-0.009	-0.17	-0.07
2001	0.010	0.18	-0.07
2002	-0.011	-0.21	-0.07
2003	-0.034	-0.62	-0.04
2004	-0.001	-0.03	-0.07
2005	0.000	-0.01	-0.07
2006	0.012	0.64	-0.04
2007	0.011	0.57	-0.05
2008	0.022	1.16	0.02
2009	0.018	0.80	-0.02
2010	0.026	1.38	0.06
2011	0.017	0.88	-0.02
2012	0.018	0.97	0.00
2013	0.017	0.88	-0.02
2014	0.027	1.53	0.08

Note: Table A.12 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of open interest on the inverse of convergence.

Table A.13: Yearly cross-sectional results of trading measures (DCOT) on price discovery

	PMPU		t-stat	Adj. R^2	MM		t-stat	Adj. R^2	SW		t-stat	Adj. R^2	OR		t-stat	Adj. R^2	NR		t-stat	Adj. R^2
Panel A: Share Variable																				
2007	-0.981	*	-2.063	0.189	0.325		0.324	-0.068	1.443		1.443	0.072	2.060		0.822	-0.024	-1.004		-0.900	-0.014
2008	-0.107		-0.203	-0.087	1.540	*	2.151	0.232	0.491		0.509	-0.066	-0.045		-0.021	-0.091	-0.677		-0.576	-0.059
2009	0.852		0.942	-0.010	-1.551		-1.067	0.012	1.157		0.746	-0.042	-2.053		-0.496	-0.074	1.196		0.639	-0.057
2010	0.463		1.000	0.000	0.342		0.406	-0.075	-0.671		-0.915	-0.014	-0.639		-0.266	-0.084	-0.387		-0.374	-0.077
2011	-0.680		-1.442	0.089	0.531		0.596	-0.062	1.093		1.264	0.051	2.320		0.861	-0.024	-1.847		-1.710	0.149
2012	0.426		0.761	-0.036	0.243		0.226	-0.086	-1.100		-0.798	-0.031	-0.958		-0.411	-0.074	1.897		1.400	0.074
2013	-0.008		-0.010	-0.111	-1.054		-0.952	-0.009	1.345		0.883	-0.022	3.709		0.933	-0.013	0.884		0.591	-0.070
2014	-0.042		-0.090	-0.110	0.075		0.118	-0.109	0.486		0.742	-0.047	-0.338		-0.175	-0.107	-0.359		-0.352	-0.096
Panel B: Trading Pressure Variable																				
2007	-0.412		-1.112	0.017	-0.607		-1.511	0.084	-0.004		-0.012	-0.077	-0.082		-0.065	-0.077	0.375		0.457	-0.060
2008	0.436		1.082	0.014	0.979	**	2.888	0.380	-0.492		-1.598	0.115	-0.203		-0.160	-0.088	1.832	**	2.274	0.258
2009	0.636		0.018	0.018	0.255		0.367	-0.085	0.189		0.273	-0.092	2.084		0.911	-0.016	0.944		0.629	-0.058
2010	0.234		0.633	-0.053	0.415		1.642	0.124	-0.501		-2.101	0.221	1.336		1.369	0.068	0.802		1.170	0.030
2011	-0.460		-0.945	-0.010	-0.494		-1.473	0.096	0.431		1.164	0.031	-2.191	*	-2.024	0.220	0.411		0.399	-0.083
2012	1.093		2.730	0.350	1.288	**	2.526	0.310	-0.388		-0.691	-0.045	2.858	**	2.362	0.276	1.754		1.280	0.051
2013	-0.244		-0.483	-0.083	-0.125		-0.249	-0.104	-0.787		-1.259	0.055	3.109	*	2.017	0.235	1.831		0.860	-0.027
2014	0.096		0.241	-0.104	0.651	*	2.250	0.289	-0.893	***	-5.681	0.758	0.851		1.415	0.091	1.288		1.622	0.140
Panel C: Propensity to Trade																				
2007	0.746		0.190	-0.074	1.526		0.630	-0.045	-1.710	*	-2.008	0.178	-2.626	**	-2.289	0.232	-0.745		-0.308	-0.069
2008	7.621	*	2.165	0.235	-0.184		-0.060	-0.091	6.073	**	3.014	0.403	0.058		0.038	-0.091	2.235		1.530	0.100
2009	12.704		1.452	0.091	3.857		1.600	0.124	0.236		0.439	-0.079	0.246		0.146	-0.098	0.752		0.187	-0.096
2010	-6.218		-1.032	0.005	-1.107		-0.653	-0.050	2.829		1.628	0.121	-0.422		-0.268	-0.084	4.271	**	3.051	0.409
2011	-2.297		-0.432	-0.080	0.999		0.380	-0.084	-2.852	**	-2.997	0.420	0.211		0.169	-0.097	0.249		0.085	-0.099
2012	-3.777		-0.624	-0.054	0.893		0.498	-0.067	4.842	**	2.582	0.321	0.284		0.168	-0.088	1.816		0.662	-0.049
2013	-1.484		-0.183	-0.107	1.156		0.627	-0.065	1.887		0.544	-0.076	-0.322		-0.166	-0.108	0.014		0.004	-0.111
2014	0.104		0.023	-0.111	1.488		0.604	-0.068	3.576	**	2.316	0.304	0.719		0.251	-0.103	5.157	*	2.100	0.254

Note: Table A.13 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of DCOT trading measures on the price discovery measure. ***, **, * denote significance at 1, 5 and 10 percent level, respectively.

Table A.14: Yearly cross-sectional results of trading measures (DCOT) on inverse of convergence

	PMPU		t-stat	Adj. R^2	MM		t-stat	Adj. R^2	SW		t-stat	Adj. R^2	OR		t-stat	Adj. R^2	NR		t-stat	Adj. R^2
Panel A: Share Variable																				
2007	1.363	*	2.027	0.172	-3.472	***	-3.300	0.397	-0.883		-0.606	-0.044	-2.981		-0.847	-0.019	0.983		0.669	-0.038
2008	0.852		1.344	0.051	-2.905	***	-3.692	0.457	0.858		0.656	-0.039	-2.898		-1.021	0.003	0.739		0.504	-0.052
2009	0.211		0.299	-0.065	-1.776		-1.700	0.112	0.495		0.430	-0.057	-2.309		-0.757	-0.029	0.527		0.369	-0.061
2010	0.794		1.033	0.071	-2.981	**	-2.698	0.295	-0.652		-0.514	-0.052	-1.702		-0.437	-0.057	1.206		0.677	-0.037
2011	0.560		0.758	-0.029	-1.412		-1.074	0.010	-0.912		-0.695	-0.036	-5.218		-1.504	0.078	0.392		0.215	-0.068
2012	0.896		1.327	0.048	-1.722		-1.387	0.058	-1.130		-0.652	-0.040	-5.045	*	-2.116	0.188	0.989		0.536	-0.050
2013	1.487	*	1.828	0.135	-2.566	*	-2.096	0.184	-3.149	*	-1.963	0.016	-3.266		-0.914	-0.011	2.281		1.348	0.052
2014	1.293	*	1.787	0.128	-1.621		-1.461	0.070	-3.186	***	-3.522	0.432	1.735		0.637	-0.041	1.330		0.748	-0.030
Panel B: Trading Pressure Variable																				
2007	0.078		0.144	-0.070	-1.121	*	-2.105	0.186	1.364	***	5.037	0.619	-2.846	*	-1.790	0.128	-2.968	***	-3.859	0.481
2008	0.108		0.190	-0.069	-1.222	**	-2.213	0.206	1.212	***	3.551	0.436	-2.674		-1.605	0.095	-2.065	*	-1.875	0.144
2009	-0.667		-1.421	0.064	-1.357	***	-3.911	0.488	1.384	***	4.321	0.541	-3.260	*	-2.010	0.169	-2.690	***	-3.050	0.356
2010	-0.560		-0.865	-0.017	-1.201	***	-3.158	0.374	1.551	***	6.155	0.711	-3.278	*	-2.080	0.182	-3.146	***	-3.386	0.411
2011	-1.076		-1.593	0.093	-1.212	**	-2.457	0.251	1.075	*	1.974	0.162	-1.250		-0.675	-0.038	-2.614	*	-1.791	0.128
2012	-0.859		-1.383	0.057	-1.778	**	-2.681	0.292	1.491	**	2.530	0.265	-3.251	*	-2.048	0.176	-3.936	**	-2.738	0.302
2013	-0.395		-0.677	-0.037	-1.125	*	-2.074	0.180	1.416	**	2.424	0.245	-2.258		-1.128	0.018	-4.017		-1.711	0.114
2014	-0.305		-0.452	-0.056	-1.464	**	-2.804	0.314	1.526	***	3.976	0.497	-2.034	*	-1.837	0.137	-2.091		-1.327	0.048
Panel C: Propensity to Trade																				
2007	-12.413	**	-2.862	0.324	-4.900		-1.586	0.092	-0.910		-0.680	-0.037	0.756		0.406	-0.059	-3.090		-0.944	-0.007
2008	-10.030	*	-2.007	0.168	2.756		0.844	-0.020	-9.015		-3.089	0.363	0.517		0.237	-0.067	-0.892		-0.445	-0.057
2009	10.508		1.491	0.075	2.709		1.343	0.051	-0.226		-0.501	-0.053	0.041		0.030	-0.071	-3.140		-1.299	0.044
2010	4.168		0.382	-0.060	2.317		1.015	0.002	-3.567		-1.095	0.013	-1.289		-0.485	-0.054	-6.765	**	-2.396	0.240
2011	-5.392		-0.682	-0.037	-1.652		-0.423	-0.058	-1.478		-0.744	-0.031	0.001		0.001	-0.071	-4.326		-0.955	-0.006
2012	0.930		0.119	-0.070	1.821		0.793	-0.025	-6.757	**	-2.855	0.323	1.872		0.890	-0.014	-2.177		-0.609	-0.044
2013	7.845		0.995	-0.001	2.325		1.038	0.005	-10.287	***	-3.252	0.390	1.184		0.517	-0.051	-5.281		-1.220	0.032
2014	-8.249		-1.176	0.025	-0.302		-0.073	-0.071	-5.426		-1.678	0.108	-0.334		-0.072	-0.071	-8.772		-1.691	0.110

Note: Table A.14 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of DCOT trading measures on the inverse of convergence. ***, **, * denote significance at 1, 5 and 10 percent level, respectively.

Table A.15: Yearly cross-sectional results of trading measures (Index Invesment) on price discovery

	IT		t-stat	Adj. R^2	IT pre		t-stat	Adj. R^2	IT PY		t-stat	Adj. R^2
2008	-0.084		-0.30	-0.11	-0.302		-0.52	-0.09	1.248		0.80	-0.04
2009	0.645		1.74	0.20	1.451		1.59	0.16	-1.858		-1.57	0.15
2010	-0.476		-1.65	0.18	-1.580	**	-2.98	0.50	0.946		0.38	-0.12
2011	-0.171		-0.74	-0.07	-0.185		-0.27	-0.15	4.815		0.86	-0.04
2012	-0.259		-0.70	-0.07	-0.659		-0.53	-0.10	8.356		0.98	0.00
2013	-1.023	**	-2.57	0.45	-1.930		-1.33	0.10	7.549		3.08	0.55
2014	-1.023	***	-4.88	0.77	-1.893	**	-2.46	0.42	7.894	***	3.73	0.65

Note: Table A.15 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of Index Trader's trading measures on the price discovery measure. ***, ** denote significance at 1 and 5 percent level, respectively.

Table A.16: Yearly cross-sectional results of trading measures (Index Invesment) on inverse of convergence

	IT		t-stat	Adj. R^2	IT pre		t-stat	Adj. R^2	IT PY		t-stat	Adj. R^2
2008	1.028	**	3.13	0.44	2.060	**	3.09	0.44	3.167	*	2.04	0.22
2009	0.680	**	2.31	0.28	1.642	**	2.42	0.31	-1.290		-1.22	0.04
2010	0.988	**	2.99	0.42	2.067	**	2.62	0.35	-3.077		-0.91	-0.02
2011	0.729		1.80	0.17	1.585		1.47	0.10	-18.735	*	-2.01	0.22
2012	0.656	*	1.97	0.28	1.752		1.56	0.20	-5.314		-0.83	-0.03
2013	0.696		1.25	0.04	0.766		0.54	-0.06	-4.700		-1.37	0.07
2014	0.369		0.65	-0.05	-0.071		-0.06	-0.09	-15.890	***	-5.06	0.67

Note: Table A.16 reports the coefficients, t-statistics, and adjusted R^2's of the yearly cross-sectional regressions of Index Trader's trading measures on the inverse of convergence. ***, **, * denote significance at 1, 5 and 10 percent level, respectively.

The Impact of Market Participants' Interaction on Futures Prices: Comparing three U.S. Wheat Futures Markets

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Working Paper

Abstract

The extreme price movements in the three U.S. wheat futures markets in 2008 and 2011 can be largely explained by fundamental developments in the world wheat market. But different price reactions in those wheat futures markets raise doubt whether only supply and demand moved wheat futures prices. The question arises whether the different behavior of market participants is also essential for price discovery. This study examines the influence of different market structures on prices of the three most important U.S. wheat futures markets. For this purpose trader's positions of the Disaggregated Commitments of Traders (DCOT) Report from June 2006 to December 2013 are analyzed. Results reveal that during the price peak, the behavior of hedgers and other market participants on the Minneapolis Grain Exchange contributed to a decoupling of wheat futures prices from the fundamental development. This demonstrates that market structure is of great importance for price development in futures markets.

***Keywords*:** Agricultural Commodity Markets, Wheat, Disaggregated Commitments of Traders, Supply and Demand.

***JEL-classification*:** G13, Q02, Q11, Q17.

1 Introduction

Several studies (e.g. Gilbert, 2010; Irwin et al., 2009; Robles et al., 2009; Stoll and Whaley, 2010) that examine the extreme rise of agricultural prices in the last decade analyze the impact of speculative activity on futures prices. Especially index trader play a key role in these studies after Masters (2008) accused this trader group to impact agricultural futures prices. While the focus of these studies is about the impact of positions changes of index traders and speculators on futures prices, returns, and volatility, this study examines the impact of the interaction between all market participants (for the following text defined as market structure) on wheat futures prices in the wheat futures exchanges in Chicago, Kansas, and Minneapolis.

Before examining the influence of market structures on wheat futures prices, the fundamental development is analyzed. The U.S. wheat market serves perfectly for this purpose because three futures markets for different wheat species exist. The most important determinant that caused prices to rise in the wheat market remains its fundamental development. Wheat futures prices peaked 2008 as a result of poor harvests, drought and export limitations by major wheat producing countries. Inventory levels were at a historical low and the demand for wheat increased slightly or remained nearly constant. This, in large part, explains rising prices. While at the end of 2002 fundamental developments also led to rising prices, the extreme increase that occurred during the crisis 2007/08 cannot be explained only by fundamental changes.

The extent to which a different market structure contributed to rising prices is analyzed by using the Disaggregated Commitment of Trader (DCOT) reports. The DCOT report differentiates between five trader categories. By this differentiated classification, the behavior of the trader categories and the resulting price pressure can be well analyzed. The results show that instead of a speculative pressure on wheat futures prices, commercials seem to contribute to a decoupling of futures prices from their fundamental development in the Minneapolis Grain Exchange.

This study proceeds as follows. First, the existing literature about pricing and speculation in agricultural commodity futures markets is discussed. Section 3 gives a market overview of the U.S. wheat market. In section 4 data, descriptive analysis, methodology, and results are presented. Section 5 summarizes the findings.

2 Literature Review

The U.S. Senate's Permanent Subcommittee on Investigations (2009) criticizes the increased trading activities of index traders in the wheat futures markets and other agricultural commodities. They claim that index traders contributed to price distortions in the wheat futures market, and that they caused increased volatility and poor convergence of spot and futures prices. While Robles et al. (2009) also find a relationship between increased index trader activity and rising grain prices, Heath (2009) and Adjemian et al. (2013) negate a relationship between index trading activity and non-convergence of wheat futures prices and their corresponding spot prices. They show that too low storage rates for the delivery instruments set by the futures exchanges caused non-convergence.

UNCTAD (2010) confirms that increased trading activity by index traders led to a decoupling of prices from their fundamental value. In a survey among physical traders and speculators, both categories agree that speculation can decouple the futures price from its fundamental value in the short-term, but in the medium- and long-term the fundamentals determine the price. One weakness of studies that find a relationship between speculative activity and commodity prices is that their argumentation is mostly based on analyzing commodity price charts and its relationship with the positions of index traders or speculators, and correlations or Granger Causality tests between these variables. The lack of methodological quality is often criticized (Stoll and Whaley, 2010; Sanders and Irwin, 2010; Aulerich et al., 2012). Nevertheless, other studies using advanced methods confirm an impact of increased speculative activity on commodity prices (Tang and Xiong, 2012; Gilbert, 2010; Singleton, 2011).

By contrast, most studies on speculation in commodity markets refute an influence on commodity prices caused by speculators. Irwin et al. (2009) show that speculative activity in recent years cannot be seen as excessive, since the level of speculative activity was not above historical averages. Sanders and Irwin (2010) find a weak positive influence of index traders on twelve agricultural commodity prices in a cross-sectional regression using weekly data. For monthly and quarterly data, increasing positions held by index traders are followed by decreasing futures prices. This confirms the results of the UNCTAD survey among practitioners that speculation can only distort commodity prices in the short-term. Sanders et al. (2010) see a positive effect from increased participation of index traders: they have a stabilizing impact on futures markets where hedgers' demand on short positions dominates. For the wheat futures markets in Kansas and Chicago, Sanders and Irwin (2011) do not find a relationship between index trader positions and futures prices. Additionally, Stoll and Whaley (2010) argue against an influence of index trading on the wheat futures market and other commodity futures markets. Brunetti et al. (2011) use highly disaggregated data on a daily base.[1] They find that hedge funds and swap dealers even stabilize the volatility of commodity futures prices in the futures market for corn. The same database is used by Aulerich et al. (2013) to analyze twelve agricultural markets at the Chicago Board of Trade (CBOT). Only a few commodities are slightly influenced by the position changes of index traders in both directions, positive and negative. For the case of the three U.S. wheat species traded in futures exchanges, Janzen et al. (2014) show that index trading contributes on a diminishingly small extent to the extreme price spikes. Thus, empirical evidence speaks against influence of index traders on wheat futures prices.

Another possibility to examine whether the sharp price increase of commodity prices during the crisis 2007/08 was caused by speculation is to test for speculative bubbles. In this case the direct influence of positions is not analyzed, but rather the relationship between futures prices and the fundamental value. Adämmer et al. (2015) and Liu et al. (2013) use the convenience yield as a proxy for the fundamental value of a commodity. While Adämmer et al. (2015) find time-dependant speculative bubbles for wheat within the last decade, Liu et al. (2013) only detect a speculative bubble for soybeans out of six agricultural commodities.

These different results can be largely explained by the usage of different methods, data and time periods. A general statement on the influence of speculation in commodity markets is hardly possible. Thus, it is of special interest to analyze one commodity in detail instead of an aggregated analysis across all commodities. Parameters as the production and inventory levels differ on a large scale between different commodities. The results of many studies show that index trading alone or speculation in general cannot be the only reason for price distortions. Another important difference between futures markets is the varying participation of different trader categories. The central question is, whether this has different effects on prices.

[1] Large Traders Reporting System = internal data of the Commodity Futures Trading Commission

Other factors impacting wheat futures prices include a U.S. Dollar Index, oil prices and equity markets. Gilbert (2010) finds an increasing influence of the oil price on grain markets after 1990. Natanelov et al. (2011) come to similar results for wheat and other agricultural commodities. Tang and Xiong (2012) show that a Dollar Index negatively impacts commodity prices, this relationship has become more pronounced since 2004. They also find an increasing importance of the S&P 500 after 2008. Giraldi (2012) demonstrates that the U.S. Dollar and the S&P 500 have an increased importance for hard red winter wheat during the period from 2007 to 2011. This is partly due to increased participation of index traders. An impact of the oil price and the U.S. Dollar on agricultural commodity prices is also detected by Abott et al. (2009). Nazlioglu (2011) finds only a non-linear relationship between oil price and the spot prices of corn and soybeans, but not for wheat. Nazlioglou and Soytas (2012) examine 24 agricultural commodities in a panel data analysis from 1980 to 2010. Their analysis show that oil prices, the U.S. Dollar and agricultural commodity prices influence each other in the short-term, whereas agricultural commodity prices are influenced by the oil price and the U.S. Dollar in the long-term.

3 Market Overview

3.1 Wheat Species

In this study, three wheat species for which futures contracts exist are examined: soft red winter (SRW), hard red winter (HRW), and hard red spring (HRS). The corresponding wheat futures contracts are the Chicago Board of Trade (CBOT) wheat futures contract for No. 2 soft red winter wheat, the Kansas City Board of Trade (KCBT) wheat futures contract for No. 2 hard red winter wheat, and the Minneapolis Grain Exchange wheat futures contract for No. 2 hard red spring. The three contracts are standardized to 5,000 bushels wheat per contract. The U.S. Senate's Permanent Subcommittee on Investigations (2009) illustrates differences among wheat species by their protein content. The higher the protein content the higher is the quality of the wheat species.[2] Hard red spring has the highest protein content of 13-14 percent. Hard red winter has a protein content of 11-12 percent and soft red winter of 9-10.5 percent. Additionally, the time of harvests differs between the three wheat species: soft red

[2] A detailed discussion addressing quality differences of the three wheat species can be found in Janzen et al. (2014).

winter and hard red winter are harvested in summer around July, while hard red spring is harvested in fall around September.

While the CBOT contract also accepts the other two wheat species for delivery, the KCBT and MGEX wheat contracts only accept hard red winter and hard red spring wheat, respectively.[3] The CBOT wheat futures contract is the most frequently traded futures contract of the three species, as shown in Table 1. The average open interest of the CBOT contract is two times higher than the open interest of the KCBT and the MGEX contract combined. In contrast to that, the average production during the marketing years 2000/01 to 2012/13 of hard red winter is the highest with 883 million bushels. During the same time period, hard red spring production is on average 480 million bushels and soft red winter 395 million bushels.

3.2 Market Fundamentals

As summarized by Trostle (2008) and Trostle et al. (2011), many events led to serious pressure on the global wheat market. The adverse weather conditions in nearly all important wheat producing countries had extreme effects on harvests in 2007 and 2010/11. Russian, Ukrainian, European, Argentinean, and Australian wheat production suffered from drought in 2007. This led to policy responses at the end of 2007 in most of the wheat exporting countries. China eliminated export subsidies and even introduced an export tax on grain products. Argentina, Russia, and Kazakhstan raised export taxes on wheat, while Ukraine restricted the amount of wheat for export. In 2010 and 2011 the sequence of events repeated. Poor harvests in several large exporting countries were followed by export restrictions. These reasons increased the demand for wheat from the U.S., where no restrictions on exports were made, but it does not completely explain the extreme increase of wheat prices. Nowadays, the global wheat demand is less dependent on U.S. wheat exports. Figure 1 shows the relative importance of U.S. exports on the global wheat market from 1960 to 2013. In 1973 the U.S. share of the world wheat exports amounted to 50.3 percent and never reached that level again with an average share of 23.3 percent from 2000-2013. An increase of demand on U.S. exports is not

[3] Contract specifications of each wheat species: *CBOT wheat*: http://www.cmegroup.com/trading/agricultural/grain-and-oilseed/wheat_contract_specifications.html; *KCBT wheat*: http://www.cmegroup.com/trading/agricultural/grain-and-oilseed/kc-wheat_contract_specifications .html; *MGEX wheat*: http://www.mgex.com/contract_specs.html.

expected to have extreme effects on prices, given that historically much higher levels were usual and world exports relatively increased.

Abott et al. (2009) document that the May 2008 estimate forecasted extremely low expected values between world stocks and world total use of wheat during the marketing year 2007/08 when prices reached a historical high. In the U.S. wheat market the relationship was even lower. This partly explains the extreme surge in prices in the U.S. wheat futures market. Wescott and Hoffman (1999) show that a large part of wheat price variability can be explained by the stocks-to-use ratio. For the estimation of the wheat price they use a model that linearly relates the wheat price to the stocks-to-use ratio. According to Marone (2008), announcements of the stocks-to-use ratio by the USDA influence both wheat spot and futures prices. Several other studies confirm a significant impact of fundamental news from the USDA on grain prices (e.g. Isengilda-Massa et al., 2008; Sumner and Mueller, 1989; Garcia et al., 1997). Therefore, at least a long-term relationship between the stocks-to-use ratio and grain prices should be apparent.

To link the fundamental development to wheat futures prices, a variation of the stocks-to-use ratio is calculated. This key figure is calculated on a yearly basis after the harvest. Instead of using the common stocks-to-use ratio, the reciprocal value is analyzed and compared to the development of wheat futures prices. A use-to-stocks ratio has the beneficial property that it is easier to compare with prices in a graph. Figure 2 shows the wheat futures price indices from the three wheat futures exchanges and the use-to-stock ratios of the corresponding wheat species. Although small deviations occur, the futures prices and use-to-stock ratios at CBOT and KCBT move similarly. The MGEX futures price completely decouples from its long-term fundamental value. Even after the fundamental situation settles down, futures prices at MGEX constantly remain above the use-to-stocks ratio. Futures prices at CBOT and KCBT recover after the situation of low inventory levels and poor harvests in 2007/08 cooled down. In Figure 3 it can be seen that the hard red spring wheat, which is the wheat species the MGEX futures contract is based on, was more exposed to increasing exports in 2008/09. But the share of exported wheat of hard red spring was already on a higher level in the four previous years and fell to a lower level than the hard red winter share of exported wheat one year after 2008/09.

So the extreme decoupling of the MGEX futures price cannot only be explained by fundamental developments, since very good harvests and lower exports in the following years should lead to a similar price decline as for CBOT and KCBT futures prices. The part of the price reaction that cannot be explained by the fundamental development, namely the possible impact of different market structures, will be examined in the following sections.

3.3 Trader Positions

If fundamental development does not explain the extreme price increase of the MGEX futures compared to the two other wheat futures contracts, it might be due to peculiarities of the futures market. As the MGEX wheat futures contract is not included in one of the two popular commodity indices, the Standard & Poor's-Goldman Sachs Commodity Index (S&P-GSCI) and the Dow Jones-UBS Commodity Index (DJ-UBSCI), the decoupling from its fundamentals cannot result from index trading. Figures 4a-c show the developments of hedgers' and all other market participants' positions on the three wheat futures markets. For a detailed analysis of the traders' actions, the long, short, and net long positions are presented separately. Additionally, in order to concentrate on the price peaks between the three wheat futures, a vertical line for the price peak is included in February 2008 and February 2011. The following differences in the behavior of hedgers and other traders on the three wheat futures markets are observed: during the year before the two price peaks, the hedgers' long positions at MGEX rise significantly. As a consequence, hedgers at MGEX are sometimes even net long. By contrast, hedgers at CBOT and KCBT only modestly increase or even decrease their long positions until the price peaks are reached. After the price peak, other market participants at CBOT and KCBT extremely decrease their long positions, especially after the second price peak. The other market participants' long positions at MGEX increase shortly after the price peak again instead. Other differences are noticed when looking at the short positions of other market participants. The short positions of other market participants at CBOT and KCBT keep stable after the first price peak and increase after the second price peak. Instead, the other market participants at MGEX decrease their short positions after both price peaks. Therefore, two incidents have surely contributed to decouple the MGEX futures price from its fundamental value: (1) the long pressure coming from the hedgers, and (2) the "failure" of other market participants at MGEX to trade the price peak away by building up short positions and reducing long positions. The next section analyzes the interaction of different market participants in more detail.

4 Empirical Analysis

4.1 Data

The data of the traders' positions from the DCOT report are publicly available on the website of the Commodity Futures Trading Commission (CFTC). They are available from June 13, 2006 on a weekly basis and differentiate the total open positions of a futures contract into *producers/merchants/processors/users* (PMPU), *swap dealers* (SW), *money managers* (MM), *other reportables* (OR), and *non-reportables* (NR). In this study the data until December 31, 2013 are used. In contrast to the often analyzed Commitments of Traders (COT) data which only differs between commercials (physical traders) and non-commercials (speculators), the DCOT data better serves for accurately assigning the motives of different trader categories.

According to the CTFC description of trader categories, the producers/merchants/processors/users hedge their exposure to the physical commodity. Swap dealers hedge their swap transactions towards physical traders or speculators. Money managers are considered as traditional speculators. They can be divided into registered commodity trading advisors (CTA), registered commodity pool advisors (CPO) or unregistered funds as hedge funds. The category other reportables consists of all traders who are obliged to report their positions because of the amount they hold, but cannot be put into one of the other groups. Additionally the DCOT reports the positions of the group *spreading*. These are the positions of swap dealers, money managers and other reportables which follow a calendar spread strategy. A calendar spread in this case means to be long and short in contracts on the same commodity but of different maturities. The group spreading will not be analyzed in this study, because it is not possible to accurately identify which contracts they hold and the motives to follow this strategy. All other traders who are not required to report because of their small amount of positions belong to non-reportables. Apart from Tokic (2012), this group is usually ignored. Because of the results from Tokic (2012), where non-reportables play an important role and the high participation as seen in Table 3, they are also considered later on.

For the empirical analysis weekly price data of wheat future contracts from the Chicago Board of Trade (CBOT - Soft Red Winter), the Kansas City Board of Trade (KCBT - Hard Red Winter), and the Minneapolis Grain Exchange (MGEX - Hard Red Spring) from June 1, 2006 to December 31, 2013 are taken from Datastream. To get a continous time series, a similar procedure to the one of Brunetti and Büyüksahin (2009) and Adämmer et al. (2011) is applied. They also base their roll-over on the liquidity of futures contracts. The returns are calculated by taking the contract in which the majority of traders are invested in, the contract with the highest open interest. If the open interest of the second-nearby contract exceeds the open interest of the first-nearby contract, the relevant contract for the return series is the second nearby contract. Although Carchano and Pardo (2009) show that different procedures to create a continuous return series lead to very similar results, the best approach is to relate the most liquid futures contract to the positions of the traders. The reported positions of the CFTC are based on all traded contracts. So it is reasonable to use the returns of the most liquid contract for analyzing the relationship between returns and positions.

Further, a Dollar Index, which represents the relation of the dollar to the seven most important currencies (Weights of the currencies in 2010: Euro: 37 percent, Yen: 30 percent, Brit. Pound: 17 percent, etc.), and the S&P 500 Composite Index as a Performance Index from June 13, 2006 to December 31, 2013 are both taken from Datastream. The WTI oil spot price for the same period is from the Energy Information Administration.

4.2 Descriptive statistics

Futures Prices

Figure 5 shows the price development of the continuous price series based on open interest on the three U.S. wheat exchanges in the time period relevant for empirical analysis. CBOT and KCBT wheat futures prices move very similar in this time period while the MGEX futures price moves away from a common trend at the end of 2007. The price peak in February 2008 is more pronounced for the MGEX futures price and does not recover to pre-crisis levels as at CBOT and KCBT. The rolling correlations between the three wheat futures prices in Figure 6 support the finding that the MGEX wheat futures price behaves very differently compared to CBOT and KCBT. The dynamic correlation between CBOT and KCBT futures returns stays constantly on a high level. Only in 2002 and 2005 did the close relationship between these two futures fall below this level. The relationship between MGEX futures returns and the futures returns on the two other exchanges is not as close. During 2008 and at the end of 2011 the correlation between MGEX futures returns and CBOT/KCBT futures returns falls below 0.4 and 0.6, respectively. Descriptive statistics in Table 2 underpin the different development of futures returns. CBOT and KCBT futures returns show negative means and are both normally distributed. MGEX futures returns are positive on average and not normally distributed. The deviation from the co-movement could be explained by a very different fundamental development of the MGEX futures contracts' underlying wheat species. But as seen in Figures 2 and 3, nothing can justify that the MGEX wheat futures price decoupled extremely from its fundamentals.

DCOT Positions

The descriptive statistics in Table 2 show a very different behavior for the growth of traders' positions between the three wheat futures exchanges. The growth of positions moves in a quite stable way at the CBOT wheat futures market. The short positions of money managers, swap dealers, and other reportables move in a far larger range than the long positions of those traders, the long and short positions of commercials and non-reportables at KCBT. In the MGEX wheat futures market, apart from the positions of commercials and non-reportables, all traders' positions move in a very unstable way as is indicated by the standard deviation, maximum, and minimum.

For further analysis it is important to consider each trader's share of open interest, since it is examined whether a relationship with futures prices exist. Table 3 shows the mean of trader's share of open interest over the whole time period. The swap dealers in the CBOT wheat futures market are highly represented in the long positions. This group is also active in the KCBT wheat futures market, albeit to a smaller extent. The long positions of the swap dealers at MGEX are playing a minor role with a total share of 3.5 percent of the total open interest for the whole period. This can be explained by index traders who are indirectly, by swap transactions, included in the category swap dealers. Minneapolis wheat is not listed on the two popular commodity indices, the Standard & Poor's-Goldman Sachs Commodity Index (S&P-GSCI) and the Dow Jones-UBS Commodity Index (DJ-UBSCI). While the commercial long positions have a small share at CBOT, the participation is significantly higher in Minneapolis with 41.9

percent. At the KCBT, the long positions are equally dispersed over the different trader categories. The share of the reporting traders is the smallest at MGEX, thus it has the largest group of non-reportables.

Summarizing, the swap dealers at CBOT dominate the long positions, but do not have large position changes. In the KCBT wheat futures market, no traders' category dominates and just the short positions of speculators and other reportables move their positions in a large range. The commercials at MGEX dominate on the long and short side, and nearly all trader categories have large position changes during the examined period on the long and the short side.

Long and Short Positions

In most studies (e.g. Robles et al., 2009; Sanders and Irwin, 2010; Brunetti et al., 2011) the net positions of the trader categories, long minus short positions, are used to analyze the influence of speculative activity. Instead, this study applies a separate analysis of long and short positions for all trader categories in the same way as Borin and Di Nino (2012) do for money managers and swap dealers. Brunetti and Büyükşahin (2009) have similar results for net positions and long and short positions separated. Gilbert (2010) criticizes studies that do not take into account long and short positions separately.

The reason for an individualized analysis is to examine each trader category's motives and expectations on both position directions instead of just focusing on the price pressure coming from the aggregated positions of speculators. Many studies analyze the net positions of index traders (e.g. Sanders and Irwin, 2011; Aulerich et al., 2013). Since index trader's short positions play a minor role, the difference between aggregated and separated analysis is marginal. In Table 4 it is obvious that this is not the case for DCOT data. An aggregated analysis of these positions would eliminate any identification of price pressure coming from one trader category. The different traders do not act as a homogeneous unit with their long and short positions which would be the case if correlations would have negative values. This shows that within each group the different directions of positions are driven by heterogeneous behavior, different motives and expectations. Especially for commercial traders, building up long or short contracts is driven by completely different motives: A producer wants to hedge his harvest by building up short positions while a bulk purchaser builds up long positions to hedge against increasing prices. Other trader categories show similar patterns to commercials when building up contracts. Even the managed money category does not act completely homogeneous, having on average a low negative correlation. Only an analysis of money manager's net position changes at CBOT can be taken into consideration with a correlation of -0.34. For this group to proceed consistently, it is assumed that building up long or short positions is driven by different motives and expectations.

4.3 Methodology

Former studies on the influence of speculation in commodity markets usually analyze a relationship between positions and futures prices graphically, by correlations or Granger Causality tests. A relationship can be detected with these procedures, but a direct causality is not necessarily involved. Positions can be adjusted by new information based on supply and demand of a commodity. The position changes would be merely a reaction to the scarcity of a commodity and thereby a channel of fundamental development rather than a sole speculative impact. At the same time, a traders' category mainly consisting of daily trend-followers would exhibit a contemporaneous correlation with prices in weekly data. Thus all methods using contemporaneous data for positions and prices have little expressive power for causality between positions and prices.

The Granger Causality test does not examine contemporaneous changes of a time series, but the influence of position changes from previous periods and its influence on prices today. On a weekly basis a lot of important information is lost, since speculators tend to trade short-term oriented. Therefore, it is unlikely that building up positions results in price pressure with one week delay. Hence, in many studies (e.g. Sanders and Irwin, 2011; Aulerich et al., 2013; Irwin et al., 2009) a relationship between positions, mostly of index traders, and prices was not detected. Grosche (2014) mentions several weaknesses coming from analyzing lead-lag relationships between positions and prices by Granger Causality tests. Thus, in this study the impact of different behavior of market participants and its indirect influence on prices is analyzed instead of a possible direct influence on prices.

To avoid omitting important factors in the analysis, the three variables Dollar Index, oil price and S&P 500 are included in the regression. Figure 7 shows the dynamic correlation between CBOT, KCBT, and MGEX wheat futures returns with the returns of a Dollar Index, oil price, and S&P 500. Evidence of increased relation between wheat prices and changes in the three factors is supported by the rolling correlations. At the beginning of the examined time period, the correlations between futures returns and factor changes are low, but at the end of 2008 the correlations between returns and factor changes begin to increase.

Oil price and S&P 500 returns are positively and Dollar Index returns negatively correlated with futures returns. The trend of the correlations with the factors and the returns on the three wheat futures exchanges is very similar. For these reasons, the futures returns are first regressed on factor changes. The part which cannot be explained by the model, the error term of this regression, is then analyzed on its relationship with position changes. The intuition behind this procedure is to filter out the logical and observed relationships with wheat futures prices, before analyzing the relationship with position changes.[4] The following VAR-model on residuals is applied to analyze the influence of position changes on futures returns:

$$lnFR_{i,t} = \alpha_i + \beta_i * \Delta lnDI_t + \gamma_i * \Delta lnOIL_t + \delta_i * \Delta lnSP_t + u_{i,t} \qquad (1).$$

$$u_{i,t} = c + \theta_i u_{i,t-1} + \sum_{k=1}^{4} \beta_{i,k}^{long} \Delta long_{i,t-k} + \sum_{i=1}^{4} \beta_{i,k}^{short} \Delta short_{i,t-k} + \varepsilon_{i,t} \qquad (2),$$

for the i grains' futures returns FR of CBOT wheat, KCBOT wheat, and MGEX wheat. DI is the Dollar Index, OIL is the oil spot price, SP is the S&P 500. u_t is the error term of regression (1), ε_t the error term of regression (2) and $long_{t-k}$ stands for logarithmic position changes of long positions, $short_{t-k}$ for the logarithmic short position changes. All returns, changes in financial factors and position changes are logarithmic differences. The variable position change is calculated as long or short position of a trader category divided by total open interest. Each trader's category long and short positions are tested separately to avoid collinearity between the position changes of different traders. The k lags for the position changes long and short span from one to four weeks in order to focus on short-term dynamics of position changes. The ideal lag number is selected by the Schwartz Criteria.

[4] Logical, because decreasing dollar elevates demand on U.S. wheat, since it is denominated in U.S. dollar. Increasing oil prices increases production costs for wheat by higher costs for fertilizer and fuel and is additionally related by biofuel demand with wheat prices. Increased prices for oil has the same effects on biofuel price and therefore incentifies farmers to cultivate other crops than wheat, which then has an effect on the wheat price because of lower cultivation. The increased relationship of equity markets and wheat price can be seen in Figure 7.

The following regressions are an extension of regression (1) and (2):

$$lnFR_{i,t} = \alpha_i + \beta_i * \Delta lnDI_t + \gamma_i * \Delta lnOIL_t + \delta_i * \Delta lnSP_t + \varphi_i^{long} * \Delta com.long_{i,t}$$
$$+\varphi_i^{short} * \Delta com.short_{i,t} + u_{i,t} \qquad (3).$$

$$u_{i,t} = \theta_i u_{i,t-1} + \beta_i^{long} \Delta long_{i,t} + \beta_i^{short} \Delta short_{i,t} + \varepsilon_{i,t} \qquad (4),$$

where $com.long_t$ are logarithmic commercial long position changes and $com.short_t$ the logarithmic commercial short position changes. The commercials are included, because they represent the part of open interest with the best information about the fundamental development of wheat. As producers, merchants, processors, and users of wheat, they have the best access to information to forecast in which direction future price development might go. Although this might not hold for small farmers, who do not have an overview over global supply and demand, the large part of the global wheat trading and processing is carried out by a small number of large merchants with research departments.[5] Regressions (2) and (4) are almost the same, while in (4) only contemporaneous position changes of all market participants except commercials are included. This clearly produces an endogeneity bias. Traders may adjust their positions on price changes instead of having an impact on prices. In this case it does not matter, because it is analyzed whether other traders than commercials also move with the price and participate in price discovery rather than having a direct impact on futures prices. If this is the case, the interaction of all participants determines the price. If no significant value for the coefficients in (4) can be observed, the price discovery is just determined by (3), which leaves the whole price determination to the factors and the commercials.

Stationarity of variables is tested according to the augmented Dickey Fuller test. Since all time series used in the regression are integrated by one, the test rejects the hypothesis of a unit root for all variables used in the regressions. As some variables are correlated, collinearity is checked by the variance inflation factor for all regressions. The highest value for the uncentered variance inflation factor is for the variance of the S&P 500 in Minneapolis in regression type (1) is 1.7, indicating that collinearity is not an issue. All regressions are based on ordinary least squares. To check for robustness of

[5] See http://www.fao.org/docrep/006/y5109e/y5109e0f.htm

the results, the residuals are tested for serial correlation (Breusch-Godfrey Lagrange multiplier test), and heteroskedascity (White's test for heteroskedasticity). If serial correlation is a problem, additional lags of the regressor are included. If residuals are heteroskedastic, robust standard errors and t-statistics are calculated.

4.4 Results

Table 5 shows the results of regression (1) and (2). There is no short-term predictability for futures returns by position changes in Chicago (CBOT). For non-reportables in Kansas (KCBT), building up short positions is followed by decreasing prices. While all the other position changes in the KCBT wheat futures market exhibit no short-term predictability, in Minneapolis (MGEX) several trading activities are significantly followed by futures returns. Building up money managers' long positions is followed by negative returns on a two week basis at MGEX. The same applies for other reportables' long positions on a weekly basis. So both trader groups, if assumed that both are trading for financial gain, are trading unsuccessfully in the short term. The biggest coefficient is for commercials' long positions. An increase of long positions is significantly followed by positive returns after one week. Whereas at CBOT and KCBT the lead-lag relationship between positions changes and returns does not show any positive coefficient, the dominance of commercials in the long positions seem to have a direct effect on price determination at MGEX.

The results of Table 6, where contemporaneous relations of position changes to the residual of regression (3) are tested, support the dominance of commercials in price discovery at MGEX. In the CBOT and KCBT wheat futures markets, money managers' and non-reportables' short positions, and swap dealers' long positions move in the opposite direction of the residual of regression (3). Additionally, non-reportables' long positions on both exchanges have significant positive coefficients. At MGEX, only the short positions of swap dealers move significantly negatively with returns. Swap dealers' short positions play a minor role, because of its small coefficient, as can be seen in Table 3. The significance can only be explained by extreme movements of the relatively small share of swap dealers' short at MGEX. After the contemporaneous position changes of the commercials are taken into account, no other trader group really takes part in the price discovery at MGEX. The large share of commercials long and no evenly matched counterpart on the short side, apart from commercial short, surely contributed to the decoupling of wheat futures prices at MGEX from its fundamental development.

5 Summary

According to current research, price formation on the wheat market has changed. The price is no longer influenced solely by the fundamental development of the commodity. Other factors like the value of the U.S. Dollar, oil prices, and the development of equity markets are of increased importance. This study provides new insights into the influence of different market structures on pricing in wheat futures markets.

Until now, there is no clear evidence of an influence on wheat prices caused by speculators or index traders. A trend-intensifying influence of speculators on prices certainly exists, but the complete influence of speculation cannot be captured by analyzing the positions of the DCOT report or any other reports provided by the CFTC. To get the accurate share of speculative influences on prices, data on each transaction and its corresponding motives would be necessary. Nevertheless, strong increases or decreases of positions, which are not justified by fundamental developments, indicate price exaggerations on the wheat futures markets. The results of this study show that the interaction of market participants can contribute to a decoupling of futures prices from the fundamental value of a commodity. The MGEX, which is mostly used by physical traders and which is not listed in the popular commodity indices, shows the highest peak of the wheat futures price and does not recover after the fundamental situation calms down. The fundamental development does not justify the large extent to which the futures price at MGEX deviates from CBOT and KCBT wheat futures prices after the peak. Whereas numerous studies concentrate on the impact of speculators and index traders, the results show that during price peaks, the behavior of hedgers at MGEX combined with the lack of other market participants trading price peaks away contributed to a decoupling of prices from the fundamental development.

Further, the results show that the increased dependency on the U.S Dollar, oil prices and equity markets contributed to changes in the price formation. During the period from the end of 2008 to end of 2012 an increased influence by these factors was observed, but it decreased again after this period. This shows that during the turbulent period of financial crisis and soaring commodity prices, the three factors were important determinants for wheat futures prices.

This study provides new findings for the U.S. wheat futures market by taking the market structure on the futures market into account. The often aggregated analyses of many commodities fail to consider these aspects. Future research focusing on the market structure and fundamental development of single commodities in detail would be of great interest. These aspects should be also considered when examining regulatory issues. The price discovery can be improved if position limits on each single future are regularly checked for their usefulness.

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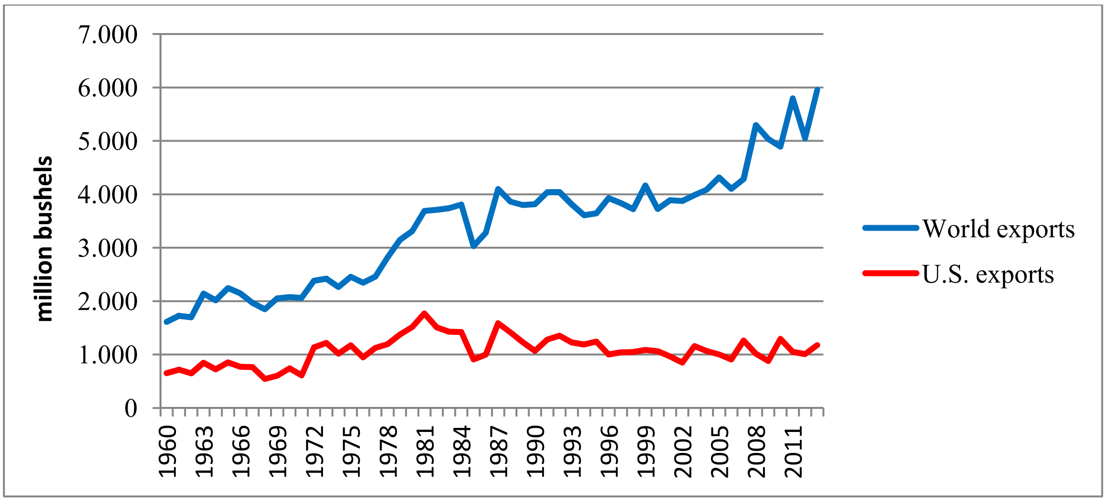
Appendix

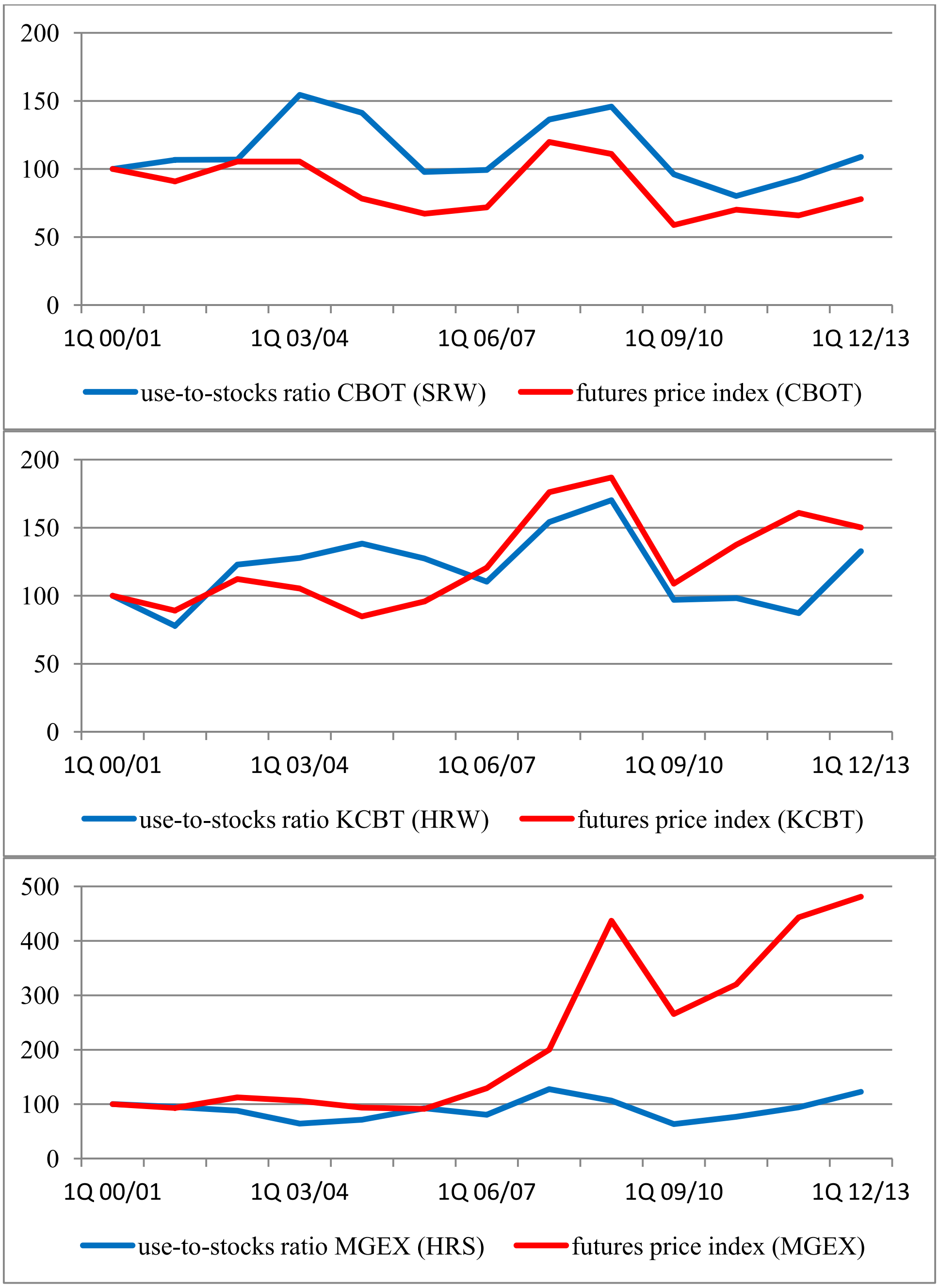
A.1 Figures

Figure 1: U.S. and World wheat exports from 1960 – 2013 (in million bushels)



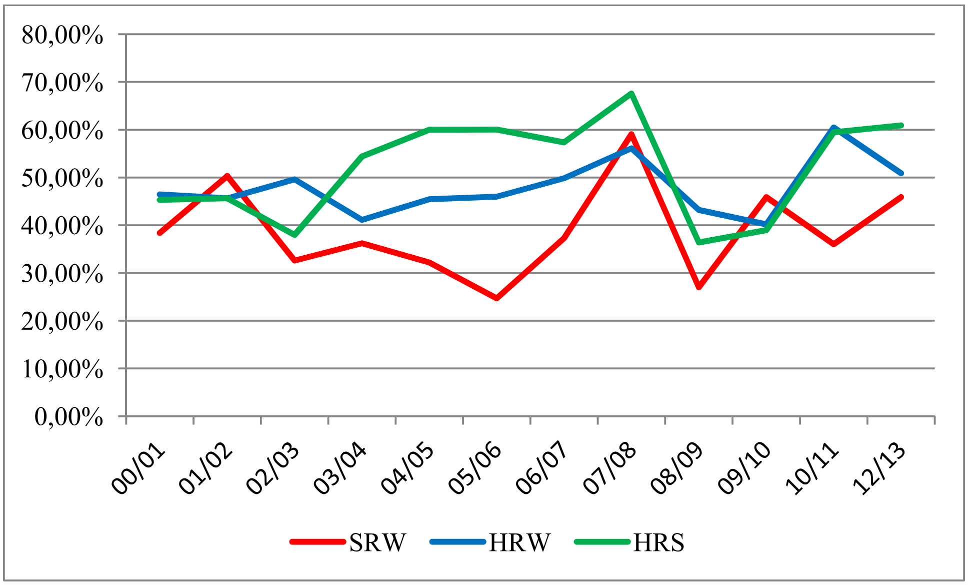
Note: Figure 1 shows the amount of wheat exported from the U.S. and the World from 1960-2013. Data are collected from U.S. Department of Agriculture (USDA).

Figure 2: Use-to-stocks ratio indices and futures price indices of the corresponding wheat species from 2000/01 to 2012/13



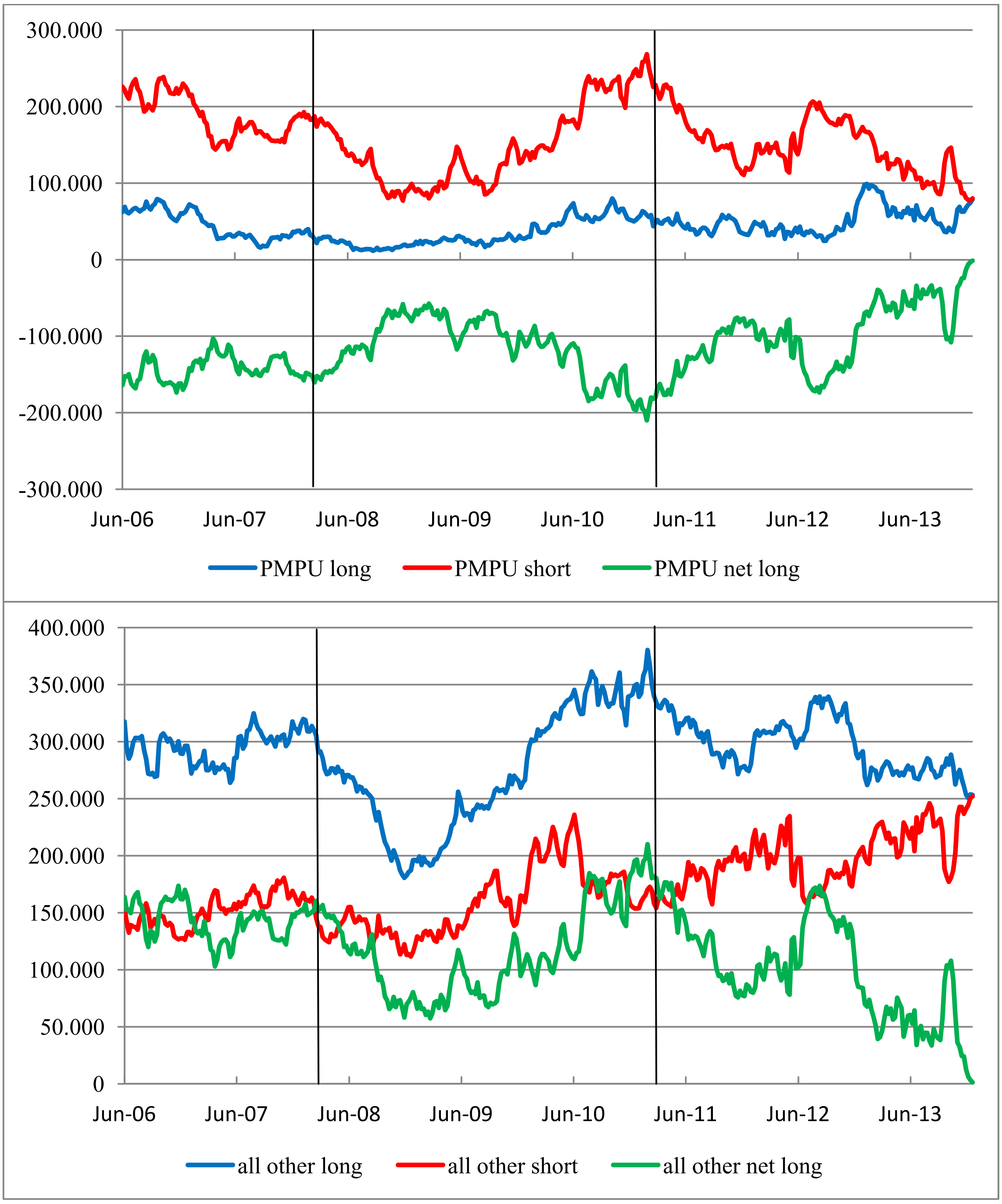
Note: The continuous future price series is a continuous index (Datastream code: CS04) provided by Datastream. Rolling yields are avoided for this continuous series by multiplying the daily returns of the near month contract with previous values of the index: $P_t = (1 + R_t) * P_{t-1}$. The data for disappearance and the ending stocks of the three wheat species are from the U.S. Department of Agriculture (USDA). The indices for yearly futures prices and the yearly use-to-stocks ratios are calculated in the same way as the continuous series from Datastream with base 100 in 2000/01.

Figure 3: Share of exported wheat for Soft Red Winter (SRW), Hard Red Winter (HRW), and Hard Red Spring (HRS) wheat from marketing year 2000/01 to 2012/13



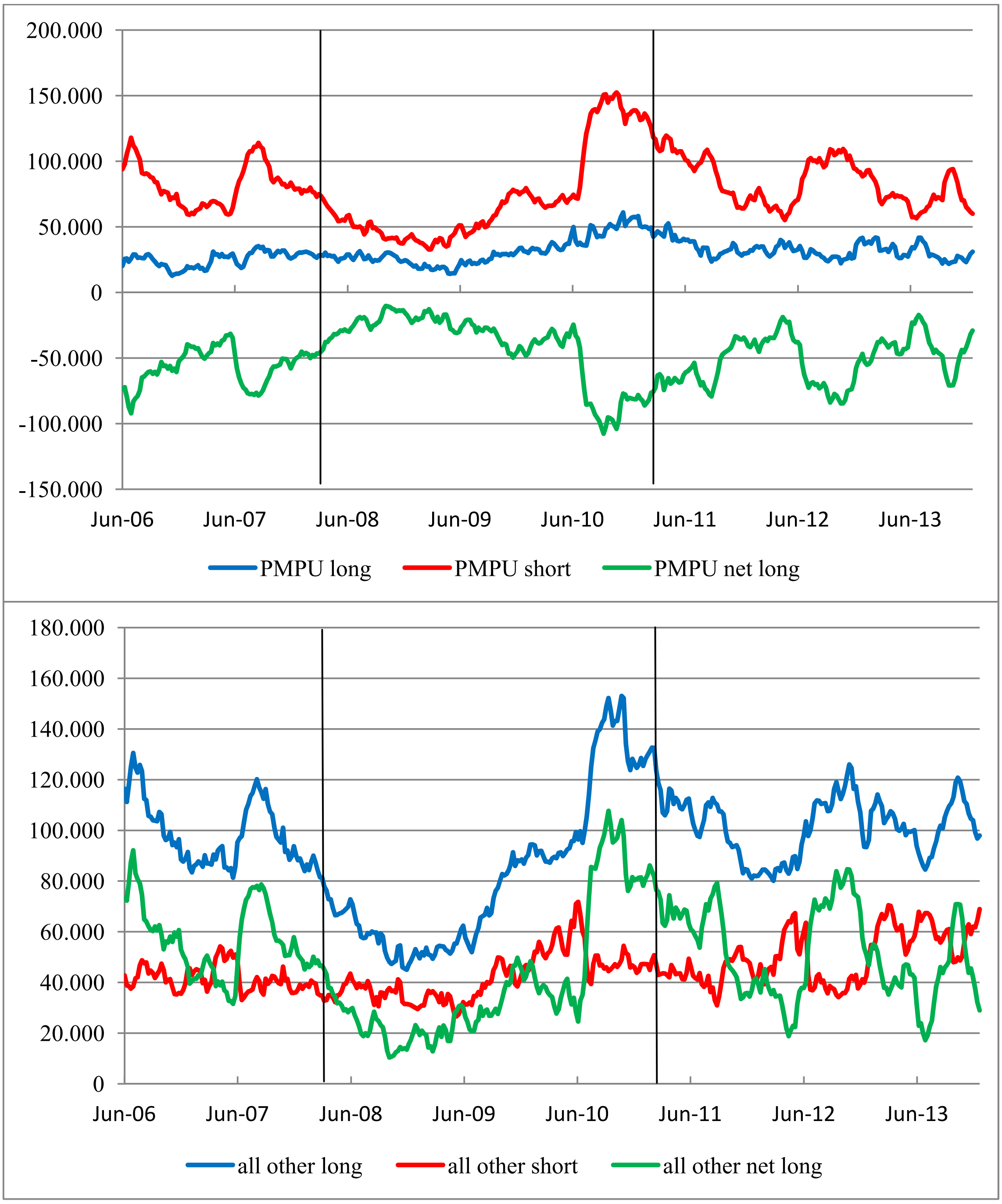
Note: For each wheat species the yearly amount of exported wheat is divided by its yearly production.

Figure 4a: Open Interest of CBOT wheat futures: Long, Short, and Net Long trader positions of Producer/Merchants/Processors/User (PMPU) and all other market participants aggregated from June 13, 2006 to December 31, 2013



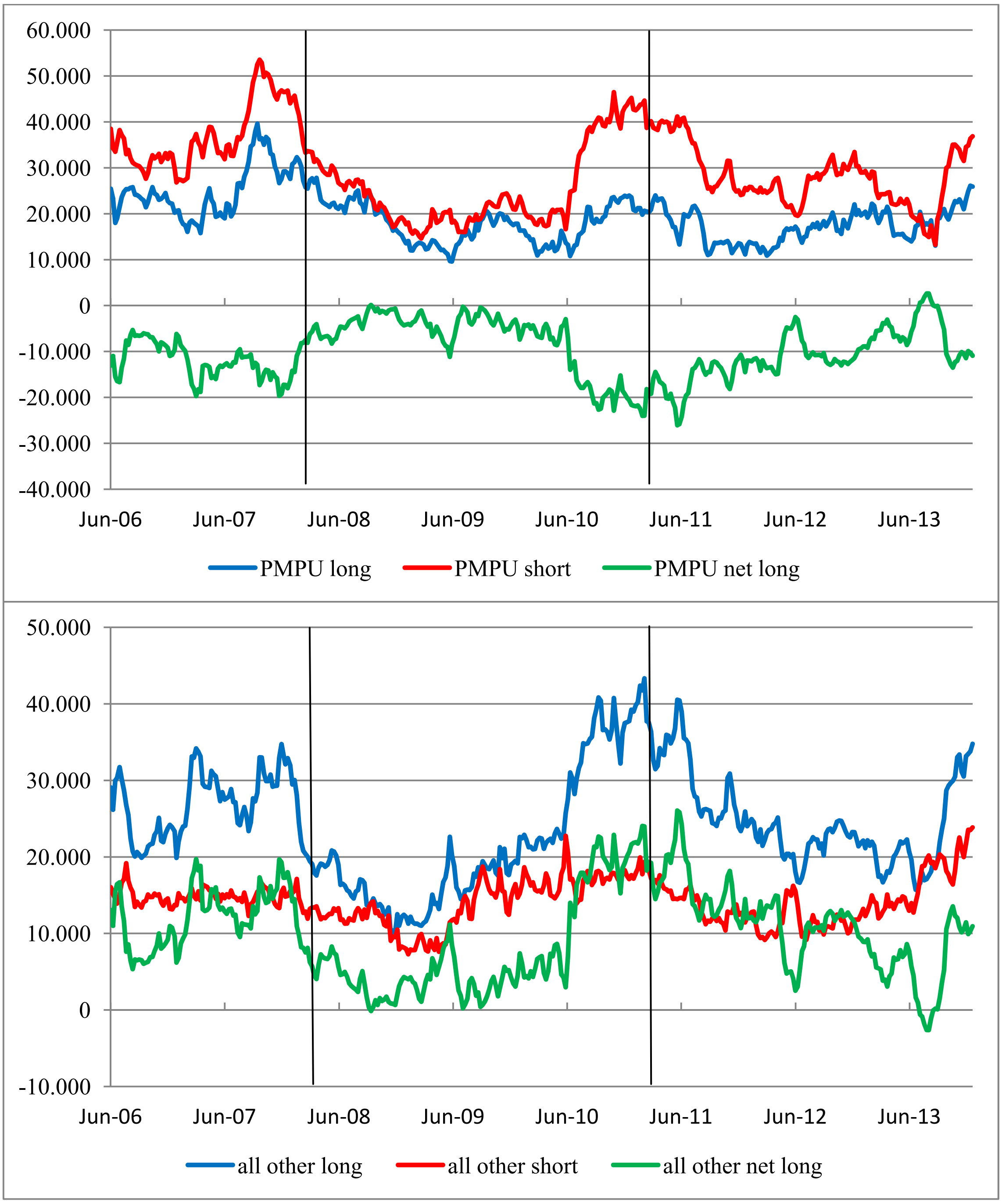
Note: The vertical lines show two price peaks in the futures price series; the first one in end of February 2008 and the second one in the beginning of February 2011. The data on positions is from the Disaggregated Commitments of Traders Report (DCOT) from the Commodity Futures Trading Commission (CFTC).

Figure 4b: Open interest of KCBT wheat futures; Long, Short, and Net Long trader positions of Producer/Merchants/Processors/User (PMPU) and all other market participants aggregated from June 13, 2006 to December 31, 2013



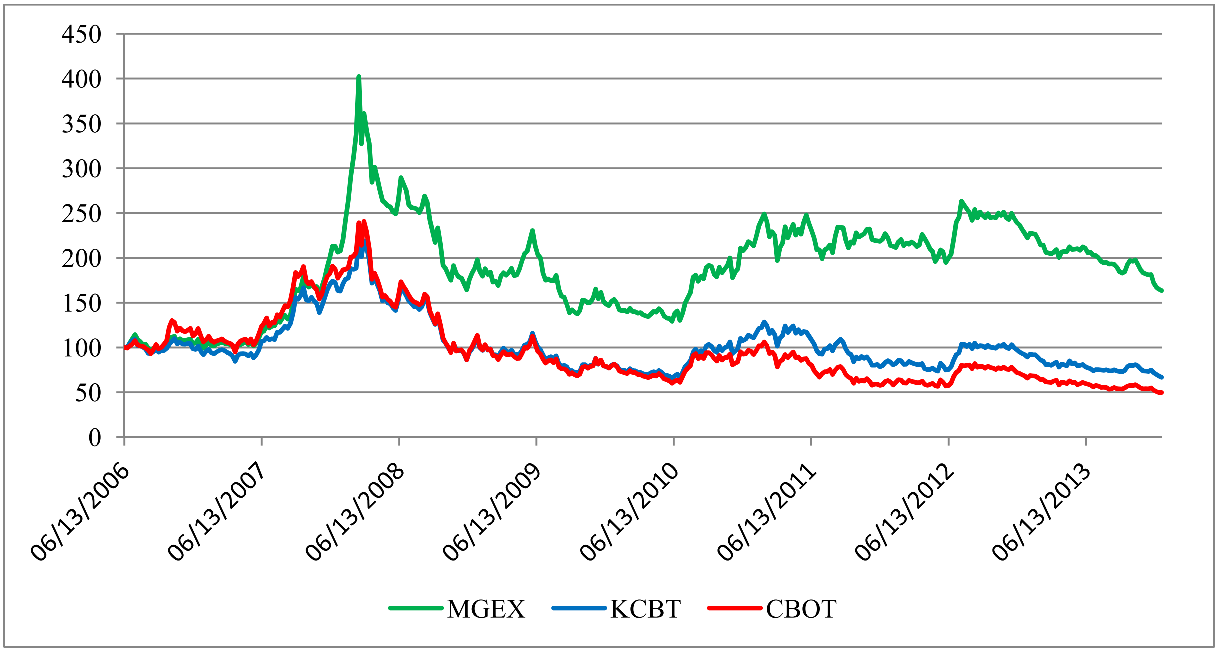
Note: The vertical lines show two price peaks in the futures price series; the first one in end of February 2008 and the second one in the beginning of February 2011. The data on positions is from the Disaggregated Commitments of Traders Report (DCOT) from the Commodity Futures Trading Commission (CFTC).

Figure 4c: Open interest of MGEX wheat futures; Long, Short, and Net Long Trader positions of Producer/Merchants/Processors/User (PMPU) and all other market participants aggregated from June 13, 2006 to December 31, 2013



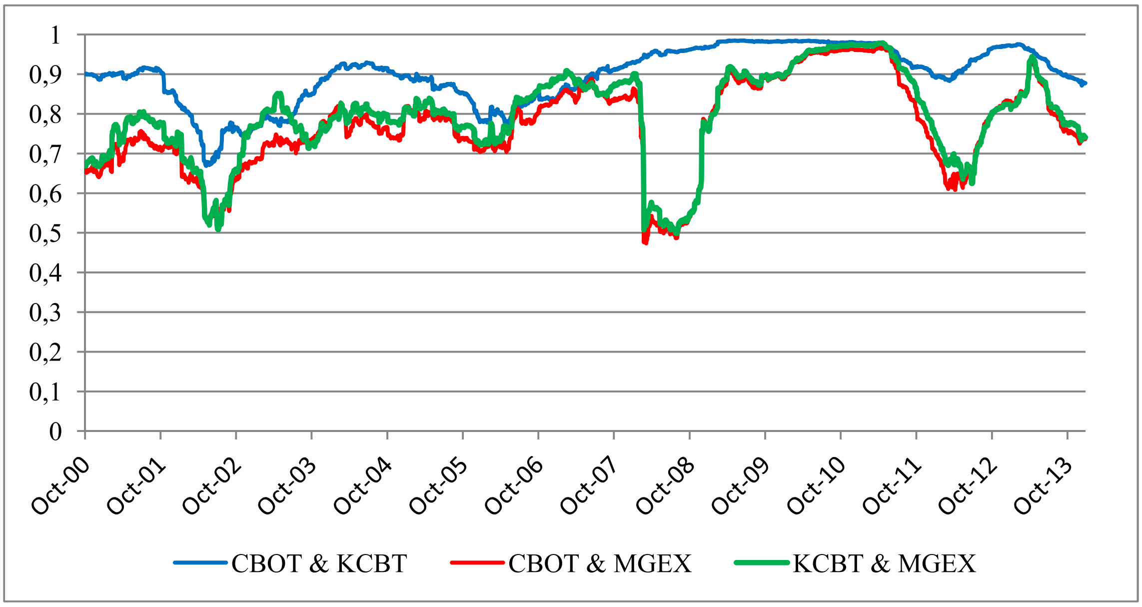
Note: The vertical lines show two price peaks in the futures price series; the first one in end of February 2008 and the second one in the beginning of February 2011. The data on positions is from the Disaggregated Commitments of Traders Report (DCOT) from the Commodity Futures Trading Commission (CFTC).

Figure 5: Wheat futures return indices of CBOT, KCBT, and MGEX from June 13, 2006 to December 31, 2013



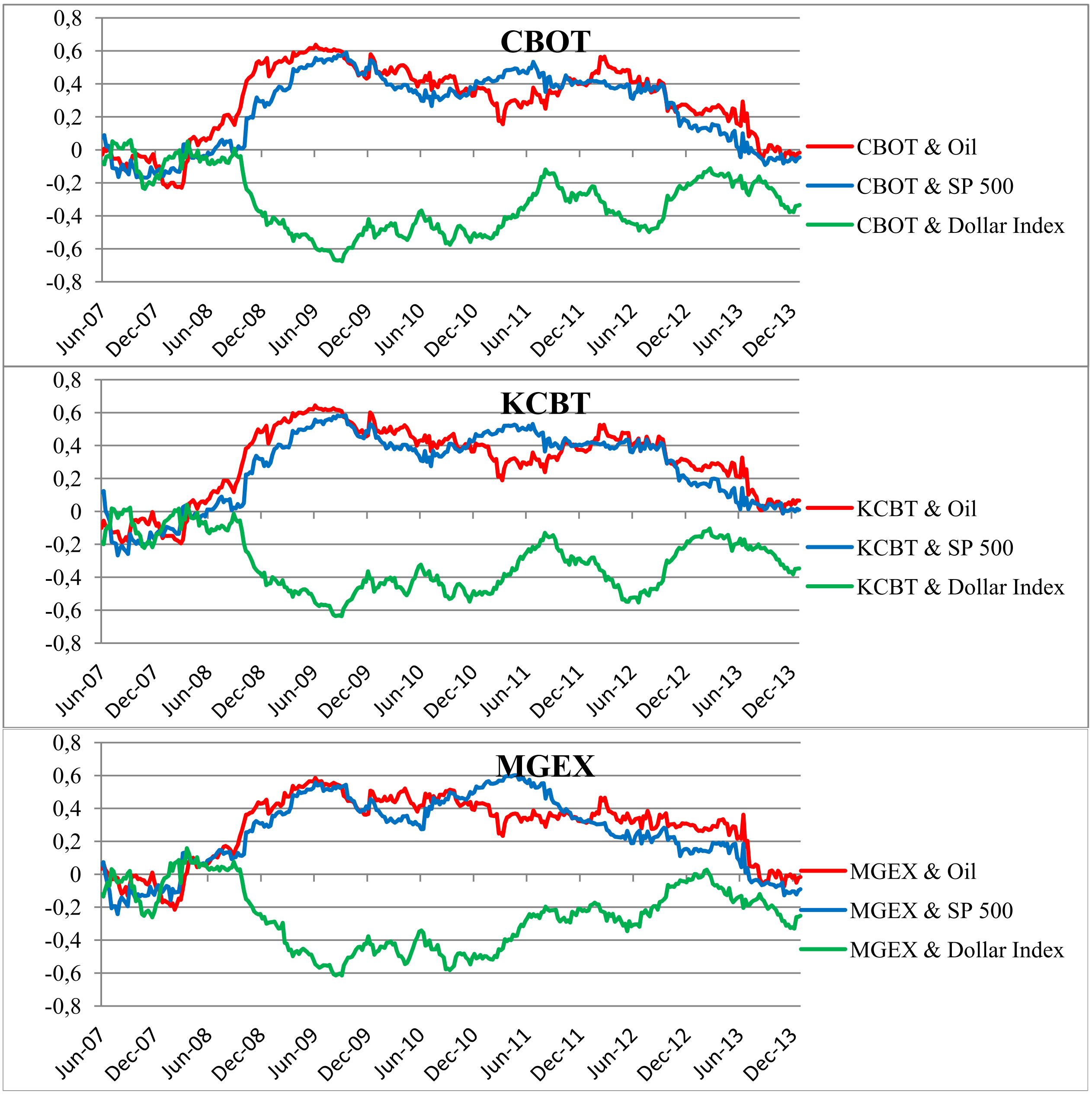
Note: The continuous price series is constructed by multiplying weekly returns of the continuous return series with previous values of the index: $P_t = (1 + R_t) * P_{t-1}$. Base date with the value of 100 for the index is June 13, 2006.

Figure 6: Rolling Correlations between CBOT, KCBT, and MGEX wheat futures returns from May 19, 2000 to December 31, 2013



Note: Figure 6 shows rolling correlations on a 200-day window between CBOT, KCBT, and MGEX wheat futures prices beginning with the first correlation value on May 19, 2000 (with returns from January 3, 2000 to May 18, 2000 = 100 days). The excess return index of Datastream is used to calculate the returns.

Figure 7: Rolling Correlations between weekly wheat futures returns and returns on Dollar Index, Oil Price, and S&P 500



Note: Figure 7 shows rolling correlations on a 50-week window between the wheat futures returns at CBOT, KCBT, and MGEX with Dollar Index, Oil Price, and S&P 500 beginning with the first correlation value on June 5, 2007 (calculated with returns from June 20, 2006 to May 29, 2007 = 50 weeks).

A.2 Tables

Table 1: Average production (in million bushels) of the three wheat species from 2000/01 to 2012/13 and average open interest of the corresponding wheat futures contracts (in thousands) from June 13, 2006 to December 31, 2013

	Soft Red Winter/ CBOT wheat	Hard Red Winter/ KCBT wheat	Hard Red Spring/ MGEX wheat
Average Production	395	883	480
Average Open Interest	411	142	47

Note: Table 1 shows the average yearly production (in million bushels) of soft red winter wheat, hard red winter wheat, and hard red spring wheat from marketing year 2000/01 to 2012/13. Data are collected from U.S. Department of Agriculture (USDA). The average open interest of the corresponding wheat futures contracts is from the Disaggregated Commitments of Traders (DCOT) Report, which is published by the Commodity Futures Trading Commission (CFTC) weekly. It represents the average of the weekly open positions (in thousands) from June 13, 2006 to December 31, 2013.

Table 2: Descriptive statistics for futures returns and position changes from June 13, 2006 to December 31, 2013

	No. of observations	Mean	Standard deviation	Max	Min	Jarque-Bera
Panel A: Chicago - CBOT						
Futures returns	394	-0.0018	0.0490	0.1479	-0.1763	4.25
MM long	394	0.0011	0.0617	0.2454	-0.2062	39.98***
MM short	394	0.0042	0.1047	0.3407	-0.5036	52.67***
SW long	394	-0.0014	0.0344	0.1293	-0.1809	115.92***
SW short	394	0.0032	0.1416	0.5483	-0.9115	592.32***
COM long	394	0.0010	0.0997	0.3745	-0.3687	12.46***
COM short	394	-0.0022	0.0568	0.3655	-0.1759	578.05***
OR long	394	0.0029	0.1275	0.6870	-0.4993	174.20***
OR short	394	-0.0004	0.0863	0.2950	-0.3519	77.95***
NR long	394	-0.0001	0.0713	0.3252	-0.2707	124.62***
NR short	394	-0.0005	0.0486	0.1653	-0.2656	107.63***
Panel B: Kansas - KCBT						
Futures returns	394	-0.0010	0.0447	0.1533	-0.1417	3.33
MM long	394	0.0000	0.0614	0.2139	-0.2371	26.70***
MM short	394	0.0055	0.5726	6.9206	-4.4881	78801.06***
SW long	394	0.0008	0.0553	0.2333	-0.2282	76.88***
SW short	394	0.0159	1.3775	7.6921	-7.2149	3172.04***
COM long	394	0.0010	0.0737	0.3157	-0.2102	19.26***
COM short	394	-0.0012	0.0402	0.2152	-0.1025	189.66***
OR long	394	-0.0017	0.1013	0.3685	-0.6401	519.11***
OR short	394	0.0031	0.2360	1.4118	-1.4171	1673.27***
NR long	394	-0.0020	0.0833	0.2833	-0.3479	41.23***
NR short	394	-0.0008	0.0601	0.2025	-0.3058	111.66***
Panel C: Minneapolis - MGEX						
Futures returns	394	0.0012	0.0425	0.1749	-0.2062	64.42***
MM long	394	-0.0012	0.1489	1.1351	-1.2128	7485.70***
MM short	394	0.0217	1.6337	6.7740	-7.0746	1216.29***
SW long	394	0.0212	0.9474	6.8778	-6.1603	16129.97***
SW short	394	-0.0002	1.2575	6.2289	-5.9860	3140.88***
COM long	394	-0.0002	0.0623	0.1891	-0.2442	31.96***
COM short	394	-0.0003	0.0406	0.2094	-0.1741	251.81***
OR long	394	0.0088	0.2229	1.0338	-1.5229	1646.45***
OR short	394	0.0062	1.1532	6.9043	-5.7489	2680.96***
NR long	394	0.0002	0.0781	0.3449	-0.3449	30.01***
NR short	394	-0.0008	0.0669	0.1902	-0.2436	3.40

Note: Table 2 shows mean, standard deviations, maximum and minimum sample values as well as results of Jarque-Bera test for normality for futures returns and weekly growth of all trader categories'(COM – Commercials, MM – Managed Money, SW – Swap Dealer, OR – Other Reportables, NR – Non-Reportables) long and short positions (divided by open interest) for Chicago, Kansas and Minneapolis futures markets. The sample period encompasses weekly data from June 13, 2006 to December 31, 2013.
***, **, * denote significance at 1, 5 and 10 percent level, respectively.

Table 3: Traders’ shares of total open positions (in %) on the exchanges CBOT, KCBT, and MGEX from June 13, 2006 to December 31, 2013

	MM		SW		COM		OR		NR	
	long	short	long	short	long	short	long	short	long	short
CBOT	17,87%	16,80%	39,14%	3,92%	10,11%	38,07%	5,07%	8,19%	8,25%	13,45%
KCBT	22,55%	7,85%	20,06%	1,03%	21,71%	54,96%	8,42%	3,77%	15,03%	20,17%
MGEX	17,75%	3,07%	3,45%	0,16%	41,94%	62,03%	6,19%	2,05%	23,82%	25,86%

Note: Table 3 shows the shares of the traders (COM – Commercials, MM – Managed Money, SW – Swap Dealer, OR – Other Reportables, NR – Non-Reportables), which are calculated as the mean of the traders’ share of open interest.

Table 4: Correlations between weekly position changes long and short

MM	SW	COM	OR	NR
		Chicago - CBOT		
-0.338***	0.096*	-0.273***	-0.180***	0.451***
		Kansas - KCBT		
-0.132***	-0.093*	-0.130***	0.081	0.706***
		Minneapolis - MGEX		
-0.078	-0.038	0.058	-0.069	0.521***

Note: Table 4 shows the correlations between position changes (COM – Commercials, MM – Managed Money, SW – Swap Dealer, OR – Other Reportables, NR – Non-Reportables), which are calculated from June 20, 2006 to December 31, 2013.
***, **, * denote significance at 1, 5 and 10 percent level, respectively.

Table 5: Results of VAR on residuals of the Factor Regression

Lag	Chicago - CBOT		Kansas - KCBT		Minneapolis - MGEX	
	Long	Short	Long	Short	Long	Short
Panel A: Money Manager Positions						
(-1)	-0.007	-0.032	0.005	0.001	0.016	0.000
	(-0.17)	*(-1.33)*	*(0.13)*	*(0.28)*	*(1.01)*	*(0.18)*
(-2)					**-0.033****	
					(-2.20)	
Panel B: Swap Dealer Positions						
(-1)	-0.079	0.005	0.006	-0.000	0.002	0.002
	(-1.20)	*(0.28)*	*(0.16)*	*(-0.04)*	*(0.77)*	*(0.90)*
Panel C: Commercial Positions						
(-1)	0.024	0.027	0.010	0.076	**0.080****	-0.074
	(1.01)	*(0.60)*	*(0.41)*	*(1.57)*	*(2.29)*	*(-1.34)*
Panel D: Other Reportables Positions						
(-1)	-0.001	0.000	0.017	-0.006	**-0.023*****	-0.000
	(-0.05)	*(0.01)*	*(1.03)*	*(-0.65)*	*(-3.68)*	*(-0.05)*
Panel E: Non-Reportables Positions						
(-1)	0.034	0.020	0.021	**-0.087***	-0.048	0.034
	(0.94)	*(0.37)*	*(0.58)*	*(-1.78)*	*(-1.43)*	*(0.89)*

Note: Table 5 reports coefficient estimates of long and short positions of each trader group and the corresponding t-statistics in parentheses.
***, **, * denote significance at 1, 5 and 10 percent level, respectively. The results of the factor regression (2) are the following (t-statistics in parentheses and adjusted R^2 after regression):

CBOT: $lnFR_t = -0.003 - 0.825 * \Delta lnDI_t + 0.193 * \Delta lnOIL_t + 0.220 * \Delta lnSP_t$
(-1.15) (-3.99) (3.76) (2.15) $R^2_{adj.} = 0.17$

KCBT: $lnFR_t = -0.002 - 0.718 * \Delta lnDI_t + 0.182 * \Delta lnOIL_t + 0.230 * \Delta lnSP_t$
(-0.89) (-3.83) (3.90) (2.47) $R^2_{adj.} = 0.18$

MGEX: $lnFR_t = -0.000 - 0.581 * \Delta lnDI_t + 0.128 * \Delta lnOIL_t + 0.244 * \Delta lnSP_t$
(-0.07) (-2.56) (2.26) (1.93) $R^2_{adj.} = 0.18$

Table 6: Results of VAR on residuals of Factor and Commercial long/short Regression

	Chicago - CBOT		Kansas - KCBT		Minneapolis - MGEX	
	Long	Short	Long	Short	Long	Short
Panel A: Money Manager Positions						
	0.054	**-0.038****	0.011	**-0.008******	0.008	-0.001
	(1.49)	*(-1.68)*	*(0.35)*	*(2.32)*	*(0.76)*	*(-1.03)*
Panel B: Swap Dealer Positions						
	-0.261******	**-0.028******	**-0.085******	0.001	0.001	**-0.004****
	(-4.76)	*(-2.04)*	*(2.31)*	*(0.80)*	*(0.69)*	*(-1.84)*
Panel D: Other Reportables Positions						
	-0.020	-0.0155	-0.0132	**0.021********	0.004	0.000
	(-1.15)	*(-0.62)*	*(-0.79)*	*(3.00)*	*(0.58)*	*(0.18)*
Panel E: Non-Reportables Positions						
	0.058	**-0.131********	**0.112********	**-0.075****	-0.0029	-0.0108
	(1.62)	*(-3.04)*	*(3.96)*	*(-1.74)*	*(-0.09)*	*(-0.34)*

Note: Table 6 reports coefficient estimates coefficient estimates of long and short positions of each trader group and the corresponding t-statistics in parentheses. ***, **, * denote significance at 1, 5 and 10 percent level, respectively. The results of the factor regression (4) are the following (t-statistics in parentheses and adjusted R^2 after regression):

CBOT:
$$lnFR_t = \underset{(-1.22)}{-0.003} - \underset{(-2.23)}{0.532} * \Delta lnDI_t + \underset{(1.76)}{0.104} * \Delta lnOIL_t + \underset{(1.81)}{0.237} * \Delta lnSP_t$$
$$\underset{(-2.90)}{-0.084} * \Delta lnCOML_t + \underset{(7.15)}{0.350} * \Delta lnCOMS_t \qquad R^2_{adj.} = 0.43$$

KCBT:
$$lnFR_t = \underset{(-0.58)}{-0.001} - \underset{(-3.06)}{0.523} * \Delta lnDI_t + \underset{(3.51)}{0.149} * \Delta lnOIL_t + \underset{(2.22)}{0.189} * \Delta lnSP_t$$
$$\underset{(-3.69)}{-0.095} * \Delta lnCOML_t + \underset{(8.03)}{0.382} * \Delta lnCOMS_t \qquad R^2_{adj.} = 0.33$$

MGEX:
$$lnFR_t = \underset{(-1.22)}{0.001} - \underset{(-1.93)}{0.343} * \Delta lnDI_t + \underset{(3.63)}{0.161} * \Delta lnOIL_t + \underset{(2.14)}{0.187} * \Delta lnSP_t$$
$$\underset{(-3.27)}{-0.103} * \Delta lnCOML_t + \underset{(5.00)}{0.240} * \Delta lnCOMS_t \qquad R^2_{adj.} = 0.20$$

The Information Content of Fundamental News vs. Traders' Positions on Grain Futures Markets: Evidence from WASDE and COT Reports

David Bosch

Working Paper

Abstract

To compare the impact of fundamental news and the publication of traders' positions in an event study framework, a generalized autoregressive conditional heteroscedasticity (GARCH) model with t-distributed error terms is applied to corn, soybeans, and wheat futures returns from January 1996 to June 2014. While fundamental news remains an important source of information for market participants in grain futures markets, results reveal that the information content of traders' positions from the Commitments of Traders (COT) report has gained importance in the corn and wheat futures market. The impact of traders' positions seems to be more pronounced in grain futures markets, where the presence of index traders is higher and those of professional speculators (money managers) lower. The impact of world fundamental news on futures prices increased after 2006, while the impact of U.S. fundamental news decreased. Interestingly, the reaction on trader's position changes is at its highest on the day of data collection, i.e. before it is made available to the public. Some traders seem to be able to anticipate large hedgers' and speculators' direction of trade.

Keywords: Event Study, Fundamental Information, Hedging, Speculation, Index Trader.

JEL-classification: Q02, Q11, G13, G14.

1 Introduction

Since the remarkable increase of index trading in commodity markets and the commodity boom during the financial crisis, a large body of literature deals with time series dependencies of index trader's positions and commodity prices in the agricultural futures market (see Robles et al., 2009; Gilbert, 2010; Sanders and Irwin, 2010; Stoll and Whaley, 2010; Sanders and Irwin, 2011; Capelle-Blancard and Coulibaly, 2011; Tang and Xiong, 2012). While it seems plausible to examine this relationship with a time series model, several problems arise, as illustrated by Grosche (2014). The findings of these studies elucidate the difficulty of getting unambiguous results about the relationship between index trading and commodity prices with standard time series models. Several studies (see Robles et al., 2009; Gilbert, 2010; Tang and Xiong, 2012) demonstrate that there is a relationship between index trader's positions and commodity prices that brings unwanted distortions to the pricing mechanism on agricultural futures markets. Contrary to these results, Sanders and Irwin (2010), Stoll and Whaley (2010), Sanders and Irwin (2011), and Capelle-Blancard and Coulibaly (2011) show that index traders do not have a significant influence on commodity futures prices. Furthermore, Sanders and Irwin (2011) point out that position limits for index traders could have destabilizing effects on the pricing mechanism in commodity markets.

When analyzing the impact of index traders on commodity futures prices, an additional problem is the lack of exact and high frequency data on fundamentals. Those data would be necessary to exclude that index traders behave rationally according to recent fundamental developments. However, fundamental data for most agricultural markets is available on a monthly base. This makes it impossible to analyze the real impact of index trading in the short-term, which might lead to price distortions from the fundamentals. This article overcomes this problem as it analyzes the price reactions on grain futures markets by comparing the impact of fundamental information with the impact of the publication of trader's positions.

Although the direct impact of index trading is not the focus of this study, it provides several new insights into pricing in grain futures markets as to the trader's positions of the Commitments of Traders (COT) reports from the Commodity Futures Trading Commission (CFTC). Furthermore, it is to my knowledge the first attempt to compare this relationship directly with fundamental information of the grains corn, soybeans, and wheat. The following questions are addressed: (1) Do USDA announcements provide new information to market participants in futures markets? (2) Do CFTC reports provide information that is relevant for pricing? (3) Has a shift in importance from fundamental information to trader's reports occurred after 2006? The former is especially important and is linked to the frequently uttered opinion that fundamentals are of less importance since index trading increased (see UNCTAD, 2011; Tang and Xiong, 2012), after Masters (2008) accused "index speculators" to distort agricultural futures prices from their fundamental value.

A shift from fundamentals to traders' positions is observed in corn and wheat futures markets, while fundamentals remain important for all grains. Additionally, I find that the information of traders' position changes is already priced in the futures market before it is made available to the public.

The study is structured as followed: After reviewing literature, data and methodology are presented. Finally, the results are described and conclusions are drawn.

2 Literature Review

According to Masters' (2008) claims, the increase of index investment decouples commodity futures prices from their fundamental value. This motivated many researchers to check whether this relationship can be verified empirically. Robles et al. (2009) show that the net positions of index traders influenced corn spot prices during the financial crisis 2006-2008 using Granger Causality tests. Gilbert (2010) finds that index investment influenced grain prices because of their additional demand for long positions in futures markets during the food price spike 2006-2008. He assumes that index traders were driven by U.S. dollar depreciation and expected growth of demand for grains from China. While Tang and Xiong (2012) do not directly test whether index traders' activity influenced commodity prices, they find that due to index trading the correlation between commodity prices increased. Treating commodities as one asset class, they emphasize that index traders caused commodity prices to decouple from their fundamental value.

By contrast, Sanders and Irwin (2010) show that index traders did not impact commodity futures prices from January 2006 to December 2008. Using cross-sectional regressions, they reject a relationship between positions, changes in net positions of index traders and returns of 12 agricultural futures prices. Similarly, Stoll and Whaley

(2010) argue against an influence of index traders on agricultural markets by Granger causality tests for data ranging from January 2006 until July 2009. In addition to standard Granger causality tests, Sanders and Irwin (2011) confirm former results of no influence of index traders on grain futures prices using long-horizon regressions. Capelle-Blancard and Coulibaly (2011) arrive at the same conclusion for 12 agricultural commodities by applying a Granger causality test with a Seemingly Unrelated Regression system. According to them, index traders did not cause a decoupling from the fundamental value during the period 2006 to 2010 or in any subperiod.

As the CFTC publishes data on traders' positions on a weekly base, studies examining dependencies between traders' positions and commodity prices lack accuracy to find out the real impact traders potentially have on the price. Some internal studies of the CFTC overcome this problem having access to highly disaggregated data on a daily basis (Brunetti et al., 2011; Aulerich et al., 2013). Nonetheless, these internal studies suffer from the same methodological weaknesses mentioned by Grosche (2012): Firstly, bivariate Granger causality tests do not prove that there is no relationship between index trader activity, commodity futures prices and volatility. Secondly, if fundamentals are not taken into account in the test, this leads to an omitted variable bias. Thus, all the above mentioned studies lack methodological precision and ignore the most important determinant of commodities, namely supply and demand.

Another possibility to examine whether commodity prices decoupled from their fundamental value is to test for speculative bubbles, as done by Liu et al. (2013), Etienne et al. (2014), Adämmer and Bohl (2015). Liu et al. (2013) use the net convenience yield as a proxy for the fundamental value. It is derived from two futures contracts with different maturities. For six agricultural commodities including corn, soybeans, and wheat, they solely find evidence for speculative bubbles in the case of soybeans. Etienne et al. (2014) relate the occurrence of bubbles to several factors, including index trader activity, speculative activity, inventories, and exports. They demonstrate that only speculators contribute to bubbles. Additionally, fundamentals as low inventories or increasing exports may lead to bubbles as well. Adämmer and Bohl (2015) rely on the crude oil price and the exchange rate to proxy the fundamentals of corn, soybeans, and wheat. For wheat, they find some evidence on the existence of speculative bubbles. Since exchange rates have a higher impact on wheat prices, they justify their findings with higher exposure of wheat to exports. Furthermore, crude oil prices have a higher impact on wheat prices since production is energy intensive. While these studies aim to capture the fundamental value of wheat, the proxies applied are far from real fundamental data. On the contrary, Etienne et al. (2014) use values directly related to fundamental data of a commodity, such as inventories and exports. But they merely measure the impact of these factors during econometrically detected bubbles. Therefore, the long-term impact of fundamental information compared to speculative activity is not being regarded.

While the impact of the publication of COT traders' positions was not considered in an event study framework, the informational value of United States Department of Agriculture (USDA) announcements was analyzed in several studies applying an event study methodology. Milonas (1987) demonstrates that the USDA announcements on crop size are a very important source of information to market participants in corn, soybeans, and wheat spot markets. Sumner and Mueller (1989) confirm the importance of USDA crop production announcements for corn and soybean futures prices.

Fortenberry and Sumner (1993) find that USDA reports had less impact on corn and soybean futures prices after 1985. One reason for the decreased importance from 1985 to 1989 as compared to the period before 1985 is that corn and soybean prices were at or near loan rates, such that building up stocks was encouraged by the government. Additionally, the introduction of options markets for corn and soybeans around 1985 shows some tendency to reduce the variability in futures markets. They conclude that the availability of options markets give traders the possibility to hedge their futures positions instead of liquidating those when unwanted market conditions appear. Garcia et al. (1997) confirm the findings of Fortenberry and Sumner (1993) that USDA reports provide important information to market participants in the corn and soybean futures markets and that this importance declined in the mid-1980s. McNew and Espinosa (1994) show that the implied volatility, derived by corn and soybean futures and option contracts, decrease significantly after the release of the USDA crop production forecasts. Thereby, they confirm the informational value of USDA reports. Egelkraut et al. (2003) compare the accuracy of USDA forecasts with production forecasts of two private agencies for corn and soybeans in the period from 1971 to 2000. They find that USDA forecasts for both grains are the most accurate with the exception of recent forecasts in August (1985-2000) and for soybeans in September. Good and Irwin (2006) confirm these findings with data up to 2005.

The results of Fortenberry and Sumner (1993) and Garcia et al. (1997) show that for more recent periods the USDA crop reports lost importance. Additionally, Egelkraut et al. (2003) and Good and Irwin (2006) find that private forecasts are more accurate in August. Assuming that these observed tendencies continued, this seems to prohibit using USDA grain reports for an event study on recent data.

Yet, according to Isengildina-Massa et al. (2008), McKenzie (2008), and Marone (2008), the tendency of declining importance of USDA reports did not continue. Isengildina-Massa et al. (2008) find that the impact of the World Agricultural Supply and Demand Estimates (WASDE) for corn and soybeans increased during the time period from 1985 to 2006. Besides, McKenzie (2008) states that USDA crop reports for corn and soybeans are still valuable information for market participants. While Marone (2008) does not generally contradict these findings, he detects that market participants on the wheat market improved in anticipating USDA announcements from 2001 to 2008 compared to the period from 1992 to 2000. The price reaction on USDA reports changed in the manner that reactions occurred on the day prior to the publication of the report.

All of the mentioned studies about fundamental information on grains aim to find an empirical justification for the financial support by taxpayers for crop reports by the USDA. This is done by checking whether USDA production forecasts are news for market participants, whether there are differences in the forecast accuracy between months, or by comparing the accuracy of USDA forecasts with forecasts of private agencies. Instead, my study focuses on the impact of WASDE projections compared to CFTC publications of trader positions on grains futures prices. Thereby, it will be of great importance to examine how the influence of fundamental data and trading developed over time. The increase of index traders' participation in commodity futures markets will be of special interest in this case.

How pricing in grain futures markets is affected by traders' positions is examined by De Roon et al. (2000). They find that hedging pressure (net short positions of hedgers) and changes in hedging pressure, which they define as price pressure, has a significant impact on futures returns. This is strongly valid for corn and wheat, and to some lower extent for soybeans. Contrary to their results, Sanders et al. (2009) find little evidence on the ability to forecast futures returns by traders' positions. Instead, the predictive power of futures returns on speculators' positions is high across all markets. To a lower extent, this also holds true for hedgers' positions. Thus, it rather appears that trend-following or positive feedback trading (see De Long et al., 1990) influences pricing in grains futures markets when compared with a direct impact of positions on pricing. As discussed by Mayer (2009), another effect may hinder to find a direct relationship between prices and positions: if position changes from informed traders, as large hedgers and speculators can be classified, are imitated by less informed traders like small speculators (a part of non-reportable traders) and index traders. Instead of gathering fundamental information, the less informed traders just follow the strategy of informed traders assuming that the initial trading decision of the informed traders was based on a detailed analysis of the fundamentals. This may lead to a decoupling of the fundamental value of a commodity if the participation of uninformed traders is high enough to impact the pricing mechanism.

3 Data

3.1 Prices

Daily futures prices for corn, soybeans, and wheat are from the Chicago Board of Trade (CBOT). The sample for futures prices ranges from January 1, 1996 to June 30, 2014. All price data is collected from Datastream. To construct a continuous time series of futures prices, contracts are rolled over depending on the size of open interest. As the futures price reaction on the publication of traders' positions is analyzed, the futures price in which the majority of traders are invested in serves perfectly for this purpose. This is usually the nearby contract. When the nearby contract comes close to maturity, the second nearby contract is the contract with highest open interest. To avoid roll-over gains or losses, returns of each contract are calculated in order to construct a return index of futures prices.

Using only nearby and next-to-nearby futures contracts ignores price reactions of futures contracts with longer maturities. Marone (2008) analyzes several futures contracts in an event study about the impact of World Agricultural Supply and Demand (WASDE) news. He finds that futures contracts with longer maturities react less sensible to WASDE announcements than short-term futures contracts. Consequently, and by reason of comparability of the impact of the publication of traders' positions and

WASDE announcements, solely the continuous futures price series based on open interest are analyzed.

3.2 Fundamental data

To analyze price reactions on fundamental news, forecasts of the USDA are used. Since September 1973, the USDA regularly publishes the World Agricultural Supply and Demand Estimates Report (WASDE).[1] This report provides detailed fundamental data on crops, which are important for grain traders and market participants in the grain futures markets. For U.S. crops, the WASDE report includes planted and harvested area, yield per harvested acre, beginning stocks, total supply and use, and ending stocks. Total supply is divided into production and imports, total use into domestic use and exports. For corn, soybeans, and wheat, these fundamental data are not only provided for the U.S., yet also for several other major exporting countries and additionally for the world. Instead of concentrating on single values like production, stocks, and total use, the stocks-to-use ratio SUR_t for U.S. and world values is calculated for the event study:

$$SUR_t = \frac{Ending\ Stocks_t}{Total\ Use_t} \qquad (1),$$

with $Ending\ stocks_t = Beginning\ stocks_t + total\ Supply_t - total\ Use_t$, and $total\ Use_t = Domestic\ Use_t + Exports_t$. The change of the values from WASDE projections are calculated by $\Delta SUR_t = SUR_t - SUR_{t-1}$. Stocks-to-use ratios are calculated for U.S. and world projections on all monthly WASDE reports from January 1996 to June 2014. This particular period was chosen for following reasons: Firstly, accurate data on single wheat futures contracts is not available before 1996. Secondly, this time period comprises two important events that caused a shift in the grains futures markets. These include the rise of index investment between 2004 and 2006[2] and the financial crisis 2007/08. These two events motivated numerous researchers to analyze the relationships between trading activity of index traders and speculators and commodity prices. By dividing the entire period into two subperiods, it is possible to shed light on whether a change in the market structure had an impact on pricing. The increased

[1] Detailed information on the procedure of the USDA to gather data on grain fundamentals can be found in Vogel & Bange (1999).

[2] Sanders & Irwin (2011) show that for corn, soybeans, and wheat the extreme rise of index trading occurred between 2004 and 2006. In this period, the long positions of index traders almost tripled for corn and wheat.

participation of index traders and the financial crisis possibly led to a shift regarding the absorption of fundamental news compared to information on traders' behavior in grains futures markets.

3.3 Traders' positions

To measure the impact of the publication of traders' positions, the Commitments of Traders Report (COT) of the Commodity Futures Trading Commission (CFTC) are used. The COT Report is published every Tuesday and separates all open positions of traders in the futures markets into positions of commercials, non-commercials and non-reportables. Commercials use futures markets to hedge risk stemming from their commercial business activities. The variable for hedgers analyzed in the event study is hedging pressure (HP). It is calculated by the number of long and short positions held by commercials:

$$HP = \frac{number\ of\ short\ hedge\ positions - number\ of\ long\ hedge\ positions}{total\ number\ of\ hedge\ positions} \quad (2),$$

which is the number of short positions minus the number of long positions held by commercials divided by the total number of positions held by commercials. While non-reportable trader hold too few positions to be included in the COT reports, the other part of reportable traders are non-commercial traders. As they do not consider futures markets for the purpose of hedging, they are typically associated with speculation. Similarly, speculative pressure (SP) is calculated by the number of long and short positions of non-commercials:

$$SP = \frac{number\ of\ long\ speculative\ positions - number\ of\ short\ speculative\ positions}{total\ number\ of\ speculative\ positions} \quad (3),$$

For each market the absolute changes in hedging pressure $\Delta HP = HP_t - HP_{t-1}$ and speculative pressure $\Delta SP = SP_t - SP_{t-1}$ are calculated.

4 Methodology

4.1 Preliminary analysis

Figures 1a-c show futures prices, hedging and speculative pressure, and stocks-to-use ratios. To compare the development of traders' positions and the fundamental development to futures prices, all graphs lie within the same time line. Speculative pressure (net long positions of non-commercials) always overtops hedging pressure (net short positions of commercials). Trading pressure of speculators and hedgers continuously move in the same direction. Speculators seem to provide sufficient liquidity to hedgers, especially in the case of corn and soybeans. Considering the case of wheat, this holds to a lower degree. When comparing futures prices, trading pressure, and stocks-to-use ratios, some relationships can be observed. In the beginning of 2004 and 2008, as well as at the end of the examined time period, increasing prices are ac-companied by increasing and high levels of speculative and hedging pressure. Moreover, the stocks-to-use ratio is reflected in the price development. During the period from 1996 until 2000, all stock-to-use ratio levels increase while futures prices decline. Although the stocks-to-use ratios and prices are also related between 2000 and 2006, the most obvious relationship for corn appears to be in 2006, for soybean mid of 2007, and for wheat gradually from mid of 2007 until the end of the year. Dramatically decreasing stocks introduce a period of an extreme upturn in prices. As the stock-to-use ratio never really recovers sustainably, price pressure remains until the end of the examined period.

Table 1 shows the descriptive statistics of futures returns. In contrast to the average soybean futures returns, average corn and wheat futures returns are negative. The soybean futures returns show the lowest volatility, whereas wheat futures returns have the highest volatility. The kurtoses of the three return samples deviate similarly from a normal distribution which indicates heavy tails. The stationarity of the analyzed variables is tested by the Augmented Dickey Fuller test that includes a drift term. The results in Table 2a and 2b show that all time series which are relevant for the empirical analysis are clearly stationary.

4.2 WASDE only

Daily commodity futures returns frequently show volatility clustering and non-normality because of a pronounced excess kurtosis. This is also the case with corn, soybean, and wheat futures returns for the examined time period in this study (see Table 1). McKenzie et al. (2004) suggest applying a GARCH (1,1) model with t-distributed error terms (GARCH (1,1)-T) when using daily commodity futures returns in an event study. They run simulations on different sample sizes of events with constant-mean return models, OLS, GARCH (1,1), and a GARCH (1,1)-T model. Due to their higher excess kurtosis in comparison to other agricultural commodity futures returns, the most suitable model with the strongest power to detect abnormal returns in the particular case of grains is the GARCH (1,1)-T model. Firstly, the GARCH (1,1)-T is applied for WASDE data only, with an event window of eleven days (±5 days from the event), and $t = 6, \dots, T-5$:

$$R_{i,t} = \alpha_i^j + \theta_i^j R_{i,t-1} + \sum_{k=-5}^{5} \beta_{i,t+k}^j D_{i,t+k}^j + \varepsilon_{i,t}^j \qquad \text{(4a).}$$

$$\varepsilon_{i,t}^j = e_{i,t}^j \sqrt{h_{i,t}^j}, \quad \text{with} \quad e_{i,t}^j \sim td(0, h_{i,t}^j, v_i^j) \qquad \text{(4b).}$$

$$h_{i,t}^j = w_i^j + \rho_i^j (\varepsilon_{i,t-1}^j)^2 + \gamma_i^j h_{i,t-1}^j, \qquad \text{(4c),}$$

for the i grains corn, soybeans, and wheat, and the j different events: all WASDE projections, only those WASDE projections with positive (negative) changes in the stocks-to-use ratios from the U.S. (world) projections, and the 20th (80th) percentile of the stocks-to-use ratios from the U.S. (world) projections. By analyzing the 20th and 80th percentiles, the impact of extreme changes in the stocks-to-use ratio can be examined separately. The mean equation (4a) of the GARCH (1,)-T model takes into account first order autoregression in the return series R_t and includes an intercept α. The coefficients β_{t+k} measure the abnormal returns of each day in the event window. The dummy variables D_{t+k} are one on the event day and the five days before and after the event, and zero otherwise. The conditional variance is modeled in the GARCH (1,1)-T model with variance h_t and with v degrees of freedom. McKenzie et al. (2004) suggest including explanatory variables in the mean equation (4a) to take non-event related variables into account, which influence commodity prices constantly. For analyzing equity prices in an event study, this would be a common stock index, as the S&P 500 for U.S. equities. In the case of grains, the dollar exchange rate, the oil price, and also the S&P 500 are three variables that could capture some variability in the commodity returns (see Tang and Xiong, 2012). But as it strikingly obvious in Figure A.1, the rolling correlations of corn, soybeans, and wheat futures returns with the dollar index, the oil price, and the S&P 500 returns show a nearly constant high correlation solely during the period from 2008 to 2010. Outside this time period the correlations are very unstable and switch from positive to negative values and vice versa. Thus, using these three explanatory variables would not improve the model in the mean equation over the whole examined time period.

The restriction on the WASDE report for an event window of eleven days has the following reason: The COT report is published every week on Friday. As a consequence, if the impact of its publication is analyzed in an event study framework and directly compared to the impact of the WASDE report, the event window has to be scaled down to a maximum of five days. Otherwise, this would result in incorrect results due to overlapping in the event window for the data on trader's positions. In the case of the COT report, restricting the event window to five days does not constitute a problem. If there is any price reaction on large traders' net position changes, it should appear on the day of the publication of the COT report or few days earlier if anticipated well. Should market participants react in a delayed way on the position changes of large traders, changes are expected to appear a day later. Instead, for the monthly WASDE report it has to be excluded that there are significant price reactions outside the event window of five days. Private firms usually publish their forecasts on grain fundamentals a few days before the WASDE report is published. Therefore, in the first stage, it is reviewed whether price reactions occurred outside the event window of five days.

4.3 WADSE vs. COT trader positions

To compare WASDE projections with the COT trader positions, the time frame in the mean equation of the GARCH (1,1)-T model is adjusted to the maximum number of days in accordance to the weekly frequency of the COT report:

$$R_{i,t} = \theta_i^{WASDE} R_{i,t-1} + \sum_{k=-3}^{1} \beta_{i,t+k}^{WASDE} D_{i,t+k}^{WASDE} + \varepsilon_{i,t}^{WASDE} \quad (5a).$$

$$R_{i,t} = \varphi_i^{COT} R_{i,t-1} + \sum_{k=-3}^{1} \beta_{i,t+k}^{COT} D_{i,t+k}^{COT} + \varepsilon_{i,t}^{COT} \quad (5b).$$

The events from the WASDE report are the same as in mean equation (4a). Accordingly, the events of the COT report are structured in the same manner as for the WASDE reports: all COT reports, positive (negative) changes in hedging (speculative) pressure, and extremely high and low values for hedging (speculative) pressure (the 80%- and the 20%-percentile of hedging and speculative pressure changes). Thus, nine different samples of events are created for both WASDE and the COT report. For both equations (5a) and (5b), the dummy variables take a value of one three days before to one day after the event day, and zero otherwise. For the comparison of WASDE projections and trader's positions in an event study, the intercept is removed in (5a) and (5b), because for the case of the COT trader reports all dummies are related to one day in a week. Using an intercept in the mean equation on COT trader positions would lead to the dummy variable trap, since every single day in the event window is captured by dummy variables.[3]

To account for the increase of index investment and the commodity boom during the financial crisis 2007/08, the whole sample is divided into two subperiods. The first subperiod ranges from January 1996 to December 2005. Figures 1a-c show that this time period does not include any extreme price changes. The second subperiod from January 2006 to end of June 2014 comprises the period where the financialization by index traders reached very high levels and when the commodity boom with its extreme price swings occurred. This procedure aims to uncover whether a shift from the importance of fundamentals of a commodity on pricing towards an increased impact of changes in large trader position occurred.

Price limits for futures prices are another important aspect. If price limits are set very low, detecting significant price reactions becomes difficult. However, price limits for the contracts are quite high.[4] In addition, McKenzie et al. (2004) state that abnormal returns can be detected by the GARCH (1,1)-T model with low returns. Even if being below one percent, the issue of price limits can be ignored.

4.4 Distributed lag model

In order to check whether the tendencies observed in the event study continue to influence futures prices over longer time periods, the relationships between fundamental news and the publication of traders' positions with futures returns are re-examined in a distributed lag model:

$$R_{i,t} = \mu_i^{WASDE} + \beta_{i,1}^{WASDE} \Delta SUR_{i,t}^{WASDE} + \beta_{i,2}^{WASDE} \Delta SUR_{i,t-1}^{WASDE} + \varepsilon_{i,t}^{WASDE} \qquad (6).$$

[3] For the WASDE report, equation (5a) was also calculated with an intercept included. In no case the intercept was significant and distinct from zero. Therefore removing the intercept for the case of WASDE projections, in the event study framework by equation (5a), does not lead to noteworthy different results.

[4] http://www.cmegroup.com/education/files/ED127_Price-Limits-FBD_8.5x11.pdf; It shows that price limits for corn were always much higher than a level that could prevent the event study model to detect abnormal returns.

$$R_{i,t} = \omega_i^{COT} + \delta_{i,1}^{COT} \Delta TP_{i,t}^{COT} + \delta_{i,2}^{COT} \Delta TP_{i,t-1}^{COT} + v_{i,t}^{COT} \quad (7),$$

with the change of the stocks-to-use ratio ΔSUR for j being U.S. or world WASDE projections, and ΔTP is the change in trading pressure from either COT hedgers or speculators. The corresponding futures return series are adjusted to the point of time when WASDE reports and COT reports are published, such that monthly returns are created for WASDE reports and weekly returns for the COT reports.

5 Results

5.1 WASDE only

To exclude important significant reactions in futures prices outside the event window for the comparison of WASDE and COT reports, Table A.1 shows the results of the event study focusing solely on the WASDE report for an event window of five days prior and after the event day. Highly positive changes in the world projections (world big) have a significant impact on all three grains outside the event window for the comparison of WASDE and COT reports. Negative futures price reactions occurred in the corn and wheat market three days after, for soybeans four days before, and for wheat additionally five days before the WASDE report is published. Earlier futures price reactions might have occurred due to publications of other providers of fundamental news. Subsequent price reactions might have taken place by virtue of delayed reactions of market participants, who do not actively monitor the WASDE reports on a daily base or just by provider of fundamental information that publish after the WASDE report. Other futures price reactions that take place outside the event window of three days prior up to a day after the event, the time frame for the comparison of the WASDE and COT report, appear to be the negative and highly negative (world small) changes in world projections for wheat. Positive price reactions occurred for negative and very negative world projection changes on wheat five days after the WASDE report is published. Soybean futures prices show a significant negative reaction on positive world projections. Thus, in any case, world projections have led to significant price reactions outside the event window when comparing the WASDE and COT reports. Generally, delayed reactions and the existence of other provider of fundamental information are possibly responsible for the significant price reactions, which are distant in time from the release of the WASDE report. The results should be kept in mind for the direct comparison of WASDE and COT reports directly in order to avoid wrong conclusions, especially when the price reaction on the WASDE report is low during the event window of three days prior the event and a day after.

5.2 WASDE vs. COT report

Considering all WASDE projections throughout the whole time period for *corn* (Table 3a), there is a negative reaction in futures prices on the event date. When separating into two subperiods, a negative reaction of the corn futures price until the end of 2005 and a positive reaction of corn futures prices thereafter are observed on the day of the WASDE publication. The impact of positive news for U.S. corn projections on futures prices decreased in magnitude and significance after 2006, while the average change of the stocks-to-use ratio was remarkably greater in the second subperiod. This also holds true for the 80th percentile of the biggest U.S. projections (U.S. big). This suggests that fundamental data on U.S. corn decreased in importance for pricing in futures markets, at least in the case of positive values. A decreasing importance of positive news for the global corn market is observed after 2006; however, contrary to U.S. projections, the average value of the projected world stocks-to-use ratios actually decreased. Hence, the decreasing reaction in prices is justified by the decreased average changes in the stocks-to-use ratio for world projections. The largest positive world projections (World big) which are expected to lower the futures price, lead to an increase of prices during the second subperiod. This paradox can be explained by the following: firstly, the world market has a minor importance for corn futures prices. Yet, if all other U.S. and world projections and their corresponding futures price reactions are compared, this conjecture does not hold. Secondly, a generally decreasing importance of fundamental data on pricing in futures markets could have led to the contradictory price reaction. While the intensity of the futures price reaction on positive and very positive news actually decreased, it does not explain why very good fundamental news lead to a positive price reaction. The most likely explanation for the positive price reaction is too optimistic expectations for the WASDE projection by market participants. While the world stocks-to-use ratio for soybeans and wheat recovers and stays on a higher level in the second subperiod, the world stocks-to-use ratio of corn remains on a low level after 2006 (see Figures 1 a-c). Market participants on the futures market probably expected a stronger recovery of corn fundamentals and therefore pushed prices as expectations were not met. The findings of the event study on the WASDE report with the wider event window show that the contradicting price reactions are reversed three days after the publication of the WASDE report (Table A.1).

While the average stocks-to-use ratios for negative U.S. and world projections lowered in the second subperiod, the reactions in the futures market increased, when summing up the significant positive reactions. The reaction of futures prices on the 20th percentile, the worst U.S. fundamental news, changed to a similar extent as the average change of the stocks-to-use ratio. Yet, the case does not apply for world projections, as the reaction of futures prices, if the significant ones are summed up, doubled in the same time where the average change of stocks-to-use ratio changed marginally. Thus, the worst negative projections of the global fundamental data appear to have the strongest influence on corn future prices after 2006.

The WASDE world projections are less important for the price reactions in the *soybean* futures market after 2006 (Table 3b). Decreasing values for world stocks-to-use ratio changes do account for the marginal futures price reactions. Positive futures price reactions on positive world stocks-to-use changes can be explained similarly as in the case of "world big" projections for corn. The low increase of stocks-to-use ratios resulted in higher prices, since expectations of market participants appear to be too optimistic on a recovery of the fundamentals. Nevertheless, the case of soybeans demonstrates that it has to be considered that the positive price reaction is repealed four days before the publication of the WASDE report (Table A.1). This happens outside the event window of the direct comparison between WASDE and COT publication. While the values of the U.S. negative and very negative average stocks-to-use ratios increase after 2006, the futures price reactions decrease slightly. In conclusion, the importance of U.S. fundamental data for soybeans decreased for pricing in futures markets, except for very good news on the U.S. stocks-to-use ratio.

In the second subperiod, the most important fundamental determinant for *wheat* futures prices is the recovery of the world stocks-to-use ratio (Table 3c). Although the average stocks-to-use ratio change is remarkably lower in the second subperiod, positive and highly positive WASDE world projections lead to the strongest price reaction after 2006. This holds especially true in the case when significant negative price reactions on world projections outside the event window of three days and one day after the WASDE publication is considered additionally (Table A.1). Negative and highly negative U.S.

and world projections do not play an important role after 2006. For negative and highly negative world projections I solely notice a significant positive price reaction five days after the WASDE report was published. The WASDE projections for the U.S. generally lost importance for pricing in wheat futures markets: Summing up the price reactions on U.S. stocks-to-use ratio changes after 2006, no significant reaction is left.

In order to describe and interpret the futures price reactions on the publication of COT position changes, it is very important to keep in mind that day 0 is a Friday when the trader positions of the previous Tuesday (-3) are published by the CFTC. During the first subperiod, the *corn* futures price reactions (Table 4a) are spread over the week: Significant futures price reactions are observed around the day of publication and around the day of data collection. Changes occur in the second subperiod: all futures price reactions, except negative net position changes of speculators, take place on the day of data collection. Hence, while the publication of positions prior to 2006 appears to be news for some market participants, after 2006 all futures price reactions take place on the day when the data on trader positions is collected. If it is assumed that neither market participants can observe the Tuesdays' position changes nor there is a leak in the procedure of collecting traders' data by the CFTC,[5] only one possible explanation remains: traders who follow the position changes of the most influential traders, as large hedgers and speculators are, successfully anticipate these position changes.

Futures price reactions change from the first subperiod to the second in a way that the reaction on positive and very positive changes in hedging and speculative pressure increases, while the magnitude of the average net position changes strongly decreases. In the case of positive net position changes, exaggerated reactions in the futures market are observed. A decrease of speculators' net long positions are of minor importance for pricing after 2006, while hedgers' net short position changes continue to influence futures pricing after 2006. In general, the futures price reactions are very similar for changes in speculative and hedging pressure, but hedging pressure is almost in any case of marginally higher magnitude than the reactions on speculative pressure. Figures 1a-c showed that speculative and hedging pressure constantly move in the same direction. Thus, the similar futures price reactions are logical. The stronger reaction on hedging

[5] According to a responsible employee of the CFTC, detailed data of the COT report will not be released before the publication on Friday without federal court order. At the same time strict confidentiality cannot be guaranteed.

pressure can be explained by the assumption that commercial traders engaged in the commodity business have better access to fundamental data than speculators, and the finding that speculators often follow momentum strategies (Kang et al. 2014; Bosch and Smimou, 2014). Therefore, it seems a more common strategy for market participants who follow net position changes of large COT traders to follow hedgers (commercials) instead of speculators (non-commercials).

Compared to the futures price reactions of COT net position changes on the corn market, the *soybean* futures market does not show any futures price reaction on the day of publication (0) before 2006 (Table 4b). Nearly all price reactions occur on the day of data collection. As all average net position changes - positive or negative - decrease after 2006, the absent or much lower futures price reactions are corollary. The positive futures price reactions on decreasing speculative and hedging pressure in the second subperiod appear somehow confusing. As data on position changes seem relevant for pricing on the soybeans futures market on the day of data collection, positive reactions on the day prior to publication seem to be a correction of the higher expected negative values for net position changes. On day -3 prior to the event day insignificantly negative, yet high, values are observed. When time moves closer to the release of the CFTC positions, the uncertainty about the value of the anticipated net position changes decreases so that the wrongly anticipated value is corrected on the day prior to publiccation. The previously mentioned offers potential to explain the futures price reaction occurring on the day of data collection in more detail. Maybe it is not the case that some market participants have access the results of the data collection. Instead, it might be due to a very good anticipation of market participants who trade according to the net long (short) position changes of speculators (hedgers).

While the COT net position changes show much lower values after 2006, most *wheat* futures price reactions increase, especially when experiencing extreme changes (big and small). A tendency of decreased importance of fundamental news and increased impact of traders' positions seems most evident in the wheat futures market. This results from the fact that in the special case of U.S. projections the importance for pricing of wheat futures is lost. A globally integrated grain market with extreme conditions in the second subperiod certainly has contributed to the finding that the relative importance of U.S. fundamental news on grains decreased.[6] The reaction day of wheat futures prices tends to be the day of data collection, as it is also the case for corn and soybeans.

Reasons for increased importance of trading pressure might be the high share of index traders (Table 5) and strikingly lower participation of professional speculators (money managers, Table 6) in the wheat market compared to the other grain markets. As index traders are rather motivated by portfolio diversification instead of a detailed analysis of single commodities, this motivation may have had a decoupling effect of wheat futures prices from the fundamental development. This conjecture is supported when price reactions and the corresponding participation of different trader categories in the corn, soybean, and wheat futures market are considered. On average, the soybean futures market has the highest share of professional speculators and the lowest share of passive traders (index traders and swap dealers). At the same time the price reactions on COT reports are the least in the soybeans futures market. Consequently, the information content of large trader's positions does not seem to be an important influence in the soybean futures market. By contrast, the wheat futures market, having a large share of index traders and swap dealers and an average share of professional speculators' net long positions near zero, is the market that shows the highest impact coming from the publication of large traders' positions. On the total ranking, the corn futures market lies within the wheat and soybean futures markets with respect to its development of price reactions on COT reports and with its participation of professional speculators, index traders, and swap dealers. These findings indicate that more index traders and less professional speculators contribute to the influence from large traders' positions on pricing in agricultural futures markets. Furthermore, this has some potential to explain that most studies analyzing the impact of index traders on agricultural futures prices do not find any economically significant relationship to returns and volatility (see e.g. Sanders and Irwin, 2010; Stoll and Whaley, 2010; Sanders and Irwin, 2011, and Capelle-Blancard and Coulibaly, 2011). While a direct influence coming from index trader positions cannot be detected, uninformed traders as index traders and swap dealers likely aggravated the extreme price developments by following the strategy of large

[6] A summary of events that led to decreased supply and inventories of global crops are summarized by Trostle et al. (2011): Adverse weather conditions in the most important grain producing countries occurred from 2005 - 2007 and 2010/11.

hedgers and speculators. This may have contributed to a decoupling of corn and wheat futures prices from their fundamental value.

5.3 Distributed Lag model

The results from the distributed lag model (Table 5a and 5b) confirm the results from the event study of the impact of fundamental news on grains futures prices for the most part: The relative importance of world projections increased in the corn and wheat futures markets from the first to the second subperiod, while this only holds to a weaker extent in the soybean futures market. Moreover, this result is supported by a decreasing impact of U.S. fundamental news on the soybean and the wheat futures market. Thus, the tendencies observed in the event study can be verified over longer horizons in a distributed lag model.

The same holds true for the relationship of futures returns with hedging and speculative pressure: From the first to the second subperiod, the impact of hedging and speculative pressure increased most evidently in the wheat futures market. Corn shows a similar tendency, but slightly lower when also considering the lagged coefficients from hedging and speculative pressure. The results for soybeans are at variance with the results from the event study. In the event study, the influence of the publication of large traders' position decreased, while the results from the distributed lag model show a slight increase of the relationship between futures returns with hedging and speculative pressure. However, in relative terms, all tendencies follow the same pattern as in the event study.

6 Conclusions

The results of the GARCH (1,1)-T event study reveal several new aspects that could not be detected by usual time series methodologies, and without taking into account the supply and demand of corn, soybeans, and wheat: The publication of the WASDE report by the USDA still provides valuable new information for market participants in grains futures markets. Particularly, the global development of stocks and use of grains has an increased impact on more recent futures prices.

A general tendency of relatively less influence of fundamental news and an increased influence of traders' positions on futures prices are observed in the case of corn and wheat. The larger share of index traders and less professional speculators could be responsible for the shift from fundamentals to traders' positions, while this conjecture is limited to the observation that price reactions on trading pressure is more pronounced in grains futures markets where index traders' and swap dealers' participation in the futures market is higher and those of professional speculators (money managers) lower. Another interesting finding is the day of significant futures price reactions on COT reports, which occurs on the day when data on traders' positions is collected. This happens to be three days before this data is published.

The findings of my study might be of interest to the CFTC in order to monitor possible cases of herd behavior and decoupling from fundamental values and its relation to the market structure. With access on internal data with higher frequencies of trader's positions compared to the publicly available weekly reports, the significant price reactions on COT reports could be assigned to traders that apply strategies as following large traders' position changes. Additionally, the price reactions on the day of data collection for the COT report should motivate those responsible for confidentiality of the data to check for possible leaks in the data collection process.

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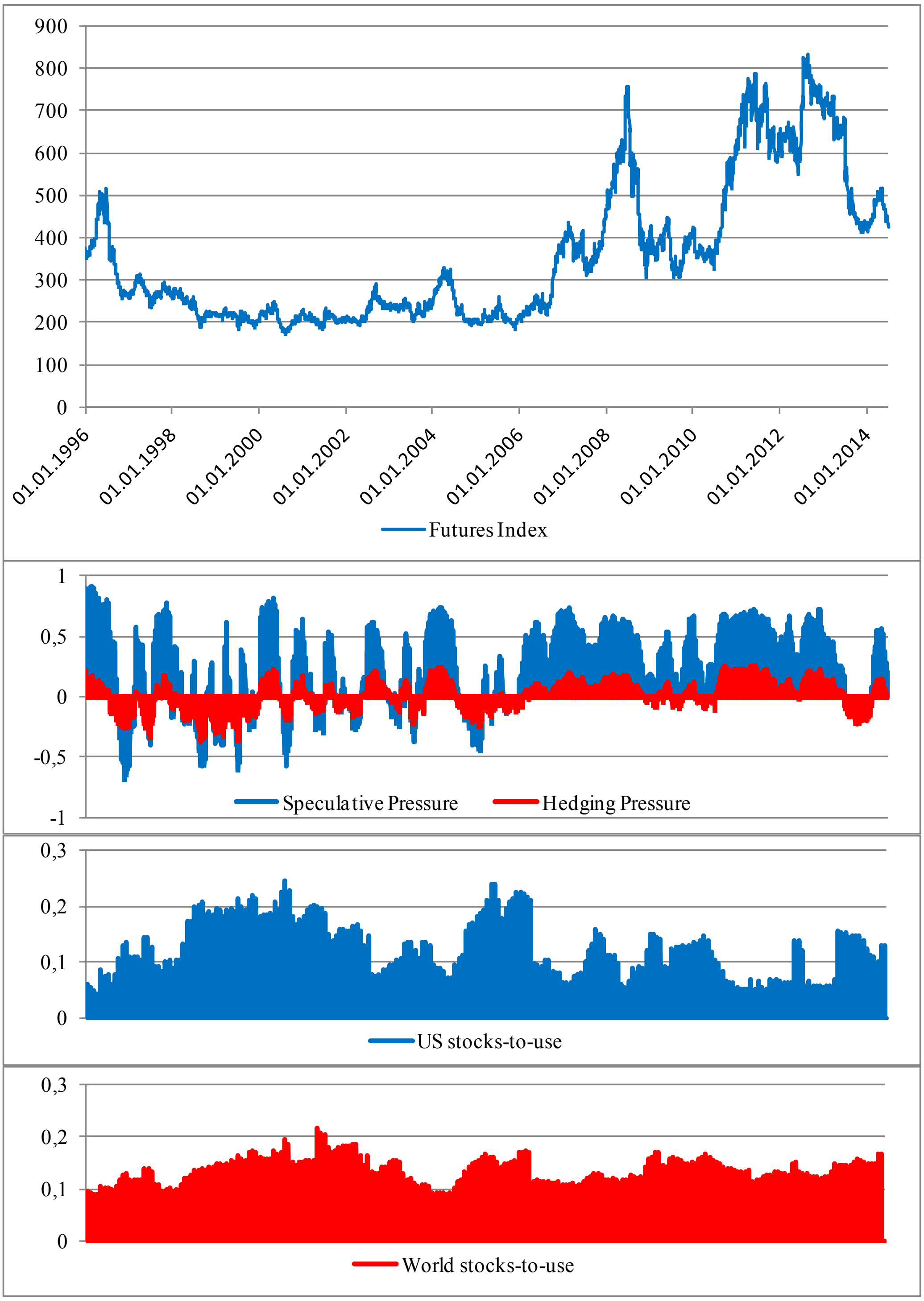
Appendix

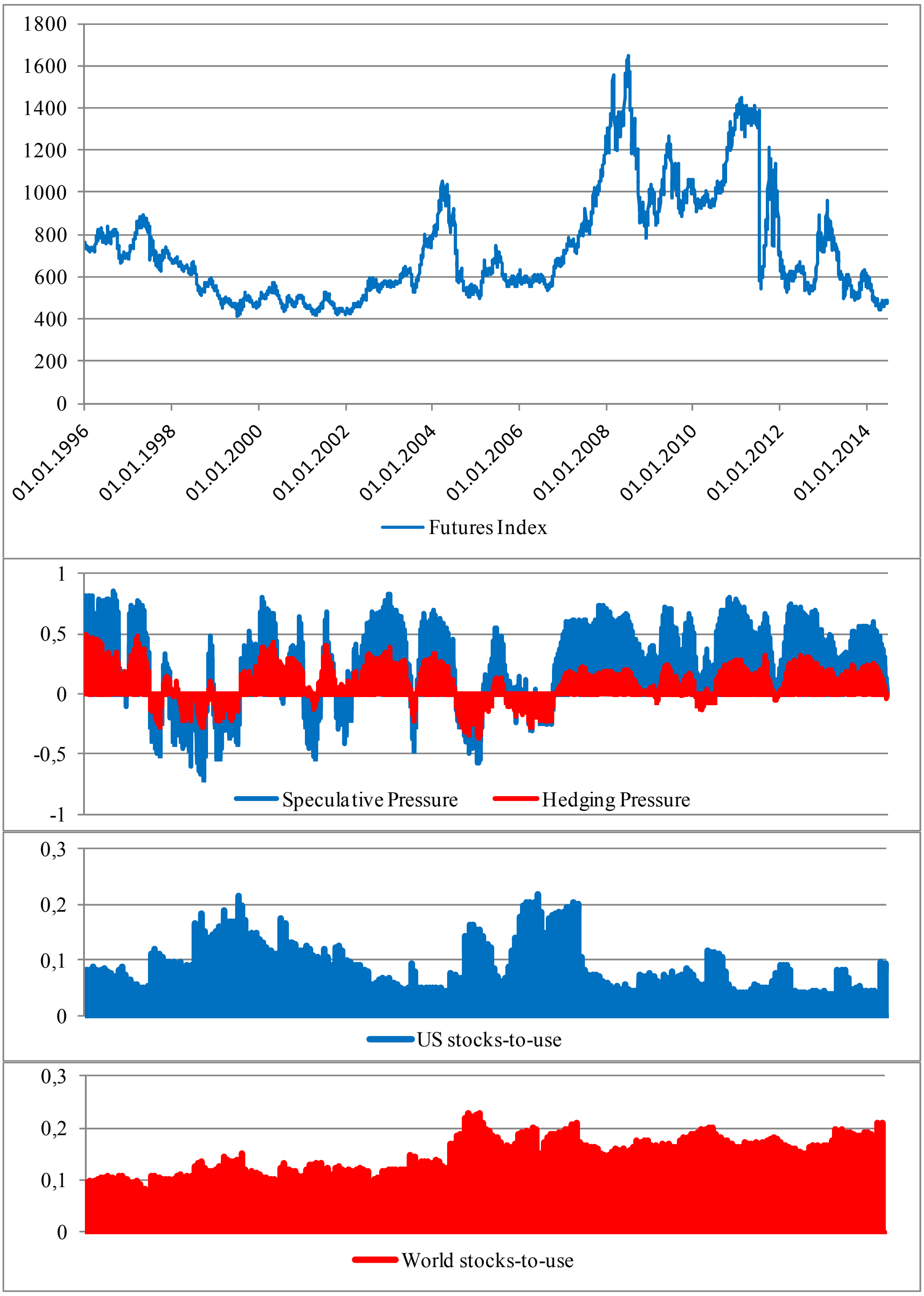
A.1 Figures

Figure 1a: Corn futures price, speculative pressure, hedging pressure and stocks-to-use ratio for U.S. and world from January 1, 1996 until June 30, 2014



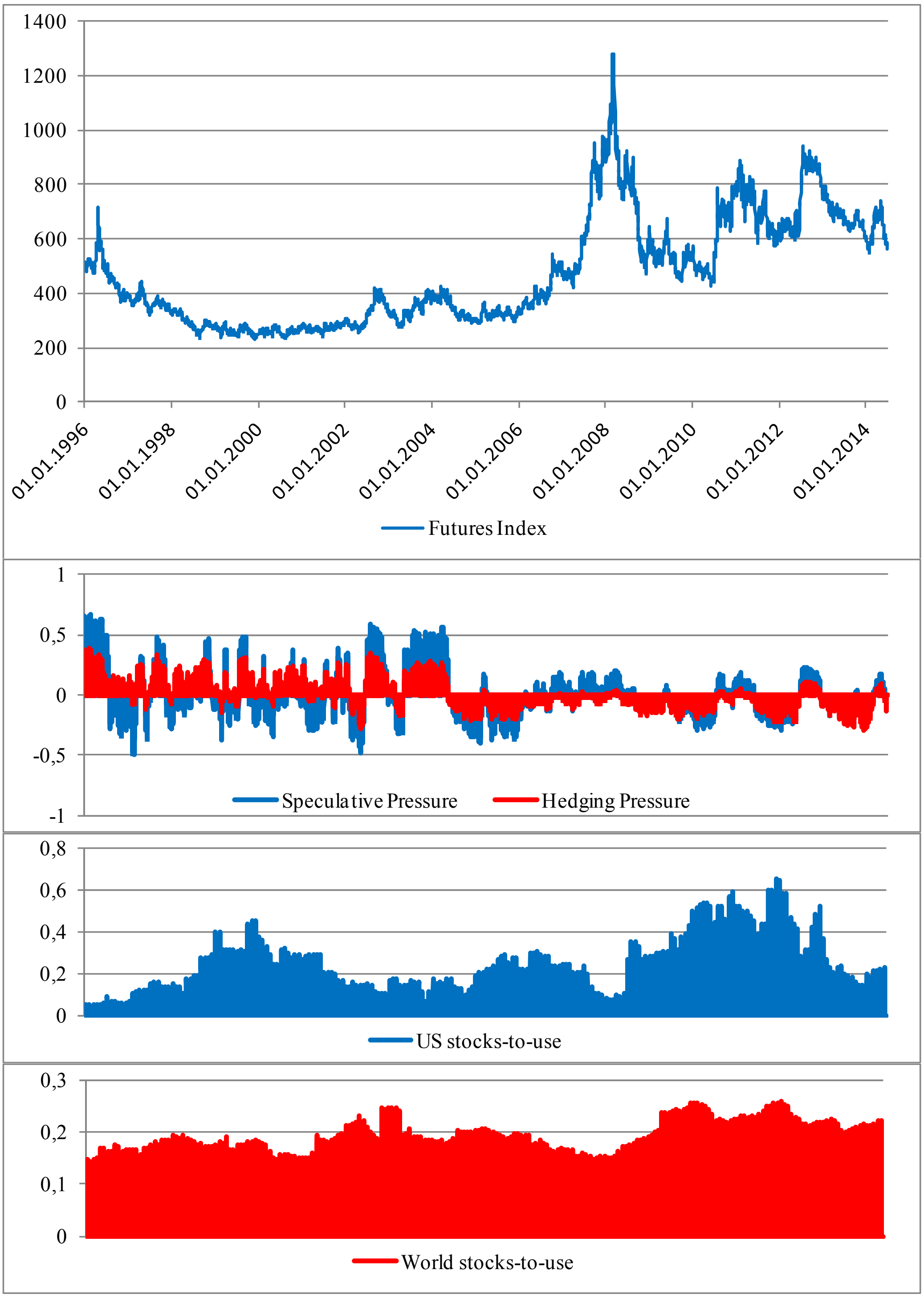
Note: The first part of Figure 1a shows the continuous futures price series for corn (continuous series by Datastream with code CS02; the rollover is based on a volume weighted procedure) from January 1, 1996 until June 30, 2014. The second part of the figure illustrates the hedging and the speculative pressure calculated as in formula (2) and (3). Part three and four are the stocks-to-use ratios for U.S. and world WASDE projections.

Figure 1b: Soybean futures price, speculative pressure, hedging pressure and stocks-to-use ratio for U.S. and world from January 1, 1996 until June 30, 2014



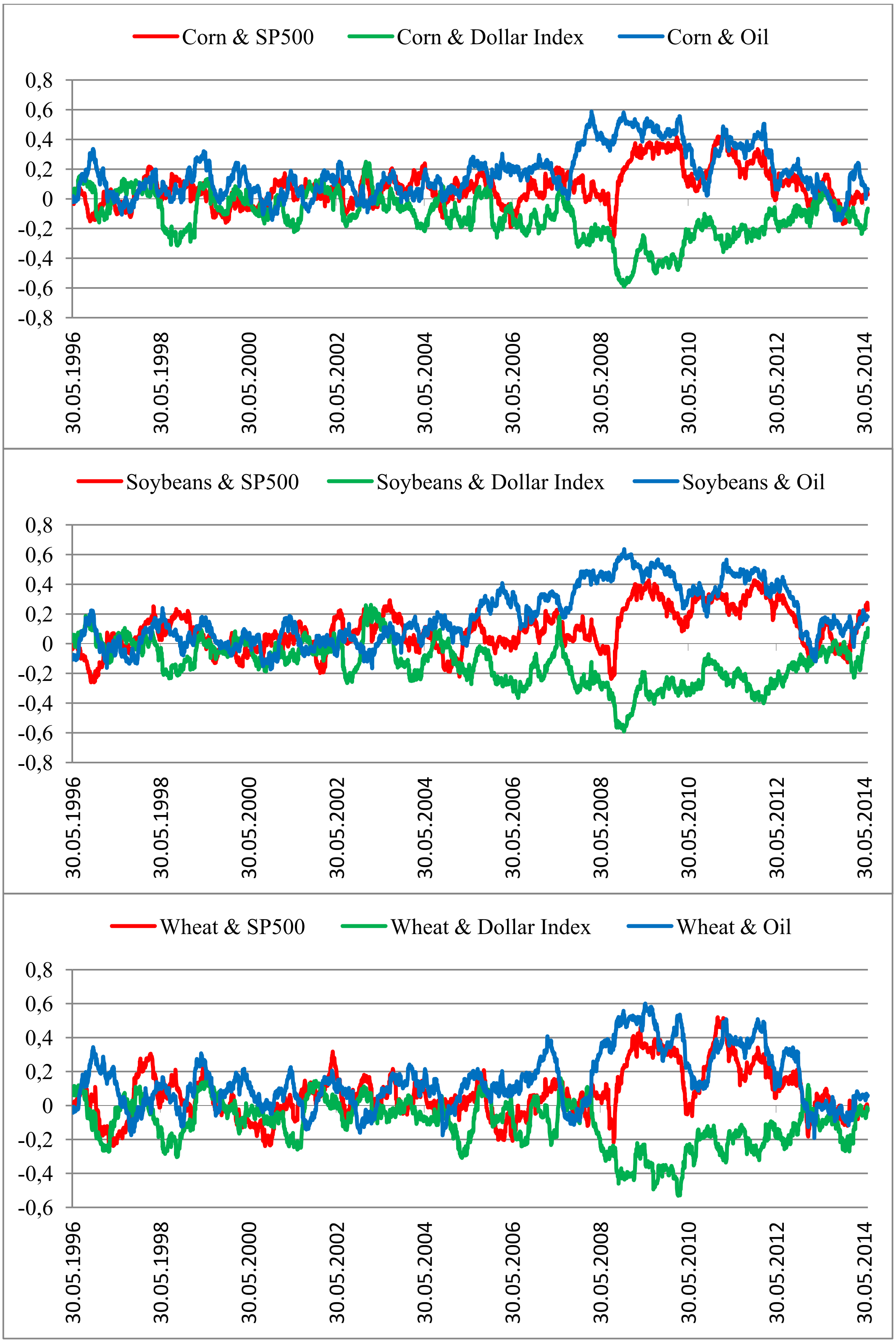
Note: The first part of Figure 1b shows the continuous futures price series for soybeans (continuous series by Datastream with code CS02; the rollover is based on a volume weighted procedure) from January 1, 1996 until June 30, 2014. The second part of the figure illustrates the hedging and the speculative pressure calculated as in formula (2) and (3). Part three and four are the stocks-to-use ratios for U.S. and world WASDE projections.

Figure 1c: Wheat futures price, speculative pressure, hedging pressure and stocks-to-use ratio for U.S. and world from January 1, 1996 until June 30, 2014



Note: The first part of Figure 1c shows the continuous futures price series for wheat (continuous series by Datastream with code CS02; the rollover is based on a volume weighted procedure) from January 1, 1996 until June 30, 2014. The second part of the figure illustrates the hedging and the speculative pressure calculated as in formula (2) and (3). Part three and four are the stocks-to-use ratios for U.S. and world WASDE projections.

Figure A.1: Rolling Correlations (200-day window) between Grains Returns and Returns of the S&P 500, the Dollar Index, and WTI crude oil



A.2 Tables

Table 1: Descriptive statistics on daily futures returns for corn, soybeans, and wheat

	Corn	Soybeans	Wheat
Mean	-0.0002	0.0002	-0.0005
SD	0.0167	0.0148	0.0184
Skewness	0.0751	-0.1838	0.0740
Kurtosis	5.2529	5.2219	5.1625
Jarque-Bera	1025***	1020***	945***

Note: 4826 observations for all price series, *** denote significance at 1% level.

Table 2a: Unit Root Tests (Augmented Dickey Fuller test) on daily futures returns, stocks-to-use ratio, hedging pressure, and speculative pressure for corn, wheat, and soybeans

	Daily futures returns	Change in Hedging Pressure	Change in Speculative Pressure	Change in US stocks-to-use ratio	Change in World stocks-to-use ratio
	Panel A: Corn				
t-statistic	-66.99***	-23.55***	-22.55***	-13.91***	-13.76***
observations	4826	966	966	222	222
	Panel B: Soybeans				
t-statistic	-69.81***	-19.39***	-24.95***	-14.03***	-14.93***
observations	4826	966	966	222	222
	Panel C: Wheat				
t-statistic	-69.48***	-25.16***	-24.35***	-13.07***	-14.72***
observations	4826	966	966	222	222

Note: *** denote significance at 1% level.

Table 2b: Unit Root Tests (Augmented Dickey Fuller test) on weekly and monthly returns

	Corn	Soybeans	Wheat
	Panel A: weekly returns		
t-statistic	-31.62***	-30.70***	-31.07***
observations	966	966	966
	Panel B: monthly returns		
t-statistic	-13.30***	-14.89***	-14.47***
observations	222	222	222

Note: *** denote significance at 1% level.

Table 3a: Corn, futures prices reaction on WASDE projections (changes in stocks-to-use ratio)

Day to event	Total USDA	U.S. positive	World positive	U.S. negative	World negative	U.S. big	World big	U.S. small	World small
Panel A: total sample (01/01/1996 – 6/30/2014)									
-3	-0.0004	-0.0013	**-0.0027****	0.0009	**0.0023***	0.0007	0.0004	0.0002	0.0012
-2	0.0007	0.0007	0.0015	0.0008	-0.0002	0.0003	0.0005	**0.0048****	**0.0053****
-1	0.0003	-0.0012	-0.0008	0.0023	0.0017	-0.0019	0.0003	0.0010	0.0020
0	**-0.0013***	**-0.0063*****	**-0.0063*****	**0.0069*****	**0.0049*****	**-0.0117*****	**-0.0069*****	**0.0223*****	**0.0133*****
1	0.0003	0.0001	0.0001	0.0010	0.0007	0.0030	**0.0042****	**0.0047****	0.0028
Panel B: 1st subperiod (01/01/1996 – 12/30/2005)									
-3	-0.0002	-0.0009	**-0.0029****	0.0011	**0.0032****	0.0007	0.0008	-0.0002	0.0013
-2	0.0007	0.0008	0.0012	0.0006	0.0001	-0.0003	0.0002	**0.0062*****	0.0037
-1	-0.0004	-0.0006	-0.0010	-0.0002	0.0004	-0.0029	-0.0012	-0.0016	0.0009
0	**-0.0034*****	**-0.0076*****	**-0.0069*****	**0.0062*****	0.0016	**-0.0128*****	**-0.0093*****	**0.0183*****	**0.0098*****
1	0.0005	0.0011	0.0010	-0.0006	-0.0001	0.0041	0.0036	**0.0052****	**0.0043***
Panel C: 2nd subperiod (01/02/2006 – 6/30/2014)									
-3	-0.0007	-0.0021	-0.0020	0.0003	0.0005	-0.0001	-0.0003	0.0012	-0.0004
-2	0.0006	-0.0001	0.0024	0.0008	-0.0011	0.0024	0.0008	0.0022	**0.0106****
-1	0.0022	-0.0034	-0.0003	**0.0056****	**0.0044***	0.0021	0.0052	**0.0063***	**0.0081****
0	**0.0033****	-0.0024	**-0.0050****	**0.0072*****	**0.0107*****	**-0.0062***	-0.0014	**0.0295*****	**0.0255*****
1	-0.0002	**-0.0045***	-0.0027	0.0027	0.0021	-0.0012	**0.0066***	0.0041	-0.0022
Panel D: Average change of stocks-to-use ratio									
total sample		0.1217	0.0476	-0.1020	-0.0403	0.2833	0.0942	-0.1839	-0.0790
1st sub		0.1006	0.0521	-0.1032	-0.0442	0.2292	0.0999	-0.1677	-0.0776
2nd sub		0.1545	0.0420	-0.1009	-0.0359	0.3572	0.0863	-0.2008	-0.0814

Note: -3 to 1 means coefficients of dummy variables from the third day prior the event on day 0 until the day after its occurrence. Total USDA: all WASDE projections, U.S. (World) positive: only WASDE U.S. (World) projections with change of stocks-to-use ratio > 0, U.S. (World) negative: only WASDE U.S. (World) projections with change of stocks-to-use ratio < 0, U.S. (World) big: only 80th percentile of the stocks-to-use ratio changes calculated with WASDE U.S. (World) projections, U.S. (World) small: only 20th percentile of the stocks-to-use ratio changes calculated with WASDE U.S. (World) projections. Coefficients of lagged returns are not reported. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Table 3b: Soybeans, futures prices reaction on WASDE projections (changes in stocks-to-use ratio)

Day to event	Total USDA	U.S. positive	World positive	U.S. negative	World negative	U.S. big	World big	U.S. small	World small
Panel A: total sample (01/01/1996 – 6/30/2014)									
-3	0.0003	-0.0003	**0.0019***	0.0008	-0.0012	-0.0019	0.0011	-0.0001	-0.0011
-2	**0.0016***	-0.0001	0.0016	**0.0031*****	0.0017	-0.0005	0.0004	**0.0035***	**0.0030***
-1	**0.0023****	-0.0004	**0.0024****	**0.0041*****	0.0021	0.0001	-0.0006	**0.0039***	0.0030
0	-0.0001	**-0.0030*****	**-0.0031*****	**0.0023****	**0.0034*****	**-0.0028***	**-0.0054*****	**0.0104*****	0.0017
1	0.0005	-0.0011	-0.0003	0.0017	0.0015	0.0012	-0.0005	0.0006	0.0029
Panel B: 1st subperiod (01/01/1996 – 12/30/2005)									
-3	0.0003	0.0004	**0.0027****	0.0003	-0.0021	0.0013	0.0032	0.0010	-0.0024
-2	**0.0018***	0.0009	0.0021	**0.0025***	0.0015	-0.0001	0.0022	0.0019	0.0024
-1	**0.0019***	**-0.0030***	0.0011	**0.0053*****	**0.0029***	-0.0025	-0.0006	**0.0060***	0.0035
0	**-0.0015***	**-0.0042*****	**-0.0046*****	0.0006	**0.0023***	-0.0019	**-0.0102*****	**0.0127*****	0.0021
1	0.0004	-0.0022	-0.0015	0.0021	**0.0027***	0.0006	-0.0025	0.0024	0.0035
Panel C: 2nd subperiod (01/02/2006 – 6/30/2014)									
-3	0.0004	-0.0012	0.0007	0.0016	-0.0001	**-0.0071*****	-0.0018	-0.0010	0.0019
-2	0.0013	-0.0012	0.0008	**0.0037****	0.0018	-0.0009	-0.0016	**0.0053***	0.0042
-1	**0.0027***	0.0031	**0.0043****	0.0023	0.0009	0.0034	-0.0002	0.0011	0.0021
0	0.0016	-0.0020	-0.0012	**0.0044****	**0.0045*****	-0.0041	-0.0010	**0.0080*****	0.0009
1	0.0005	-0.0001	0.0013	0.0010	-0.0002	0.0020	0.0020	-0.0017	0.0016
Panel D: Average change of stocks-to-use ratio									
total sample		0.1642	0.0473	-0.0914	-0.0367	0.3374	0.0968	-0.1742	-0.0700
1st sub		0.1637	0.0563	-0.0865	-0.0434	0.3352	0.1147	-0.1610	-0.0676
2nd sub		0.1648	0.0366	-0.0974	-0.0289	0.3401	0.0745	-0.1868	-0.0757

Note: -3 to 1 means coefficients of dummy variables from third day prior the event on day 0 until the day after its occurrence. Total USDA: all WASDE projections, U.S. (World) positive: only WASDE U.S. (World) projections with change of stocks-to-use ratio > 0, U.S. (World) negative: only WASDE U.S. (World) projections with change of stocks-to-use ratio < 0, U.S. (World) big: only 80th percentile of the stocks-to-use ratio changes calculated with WASDE U.S. (World) projections, U.S. (World) small: only 20th percentile of the stocks-to-use ratio changes calculated with WASDE U.S. (World) projections. Coefficients of lagged returns are not reported. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Table 3c: Wheat, futures prices reaction on WASDE projections (changes in stocks-to-use ratio)

Day to event	Total USDA	U.S. positive	World positive	U.S. negative	World negative	U.S. big	World big	U.S. small	World small
Panel A: total sample (01/01/1996 – 6/30/2014)									
-3	-0.0004	-0.0003	**-0.0031****	-0.0004	0.0026	0.0013	-0.0020	0.0022	0.0029
-2	0.0005	-0.0001	-0.0007	0.0016	0.0018	0.0003	-0.0009	0.0001	0.0029
-1	0.0014	0.0008	-0.0010	0.0024	**0.0040*****	-0.0007	-0.0024	0.0036	**0.0065*****
0	**-0.0043*****	**-0.0062*****	**-0.0081*****	-0.0008	-0.0002	**-0.0078*****	**-0.0067*****	**0.0040***	0.0019
1	-0.0011	-0.0005	-0.0011	-0.0023	-0.0012	0.0003	0.0007	-0.0008	-0.0024
Panel B: 1st subperiod (01/01/1996 – 12/30/2005)									
-3	0.0004	-0.0006	-0.0019	0.0028	0.0027	0.0008	-0.0015	0.0044	0.0039
-2	0.0008	0.0009	0.0009	0.0006	0.0007	0.0001	-0.0020	-0.0025	0.0025
-1	0.0007	-0.0004	-0.0021	0.0032	**0.0035***	**-0.0060****	-0.0039	0.0037	**0.0064*****
0	**-0.0036****	**-0.0056*****	**-0.0072*****	0.0013	-0.0001	**-0.0069****	**-0.0048****	**0.0057****	0.0030
1	0.0001	0.0005	0.0012	-0.0014	-0.0013	-0.0003	0.0007	-0.0001	-0.0023
Panel C: 2nd subperiod (01/02/2006 – 6/30/2014)									
-3	-0.0020	0.0004	**-0.0054****	-0.0045	0.0025	0.0023	-0.0039	-0.0006	0.0006
-2	-0.0002	-0.0025	-0.0032	0.0024	0.0038	0.0015	0.0025	0.0036	0.0033
-1	0.0026	0.0038	0.0006	0.0013	**0.0052***	**0.0086****	0.0033	0.0033	0.0064
0	**-0.0057*****	**-0.0083*****	**-0.0098*****	-0.0032	-0.0002	**-0.0101*****	**-0.0127****	0.0018	-0.0007
1	-0.0031	-0.0029	**-0.0048****	-0.0033	-0.0007	0.0014	-0.0055	-0.0018	-0.0021
Panel D: Average change of stocks-to-use ratio									
total sample		0.1099	0.0272	-0.1210	-0.0243	0.3152	0.0548	-0.1850	-0.0443
1st sub		0.0982	0.0353	-0.1290	-0.0257	0.3175	0.0649	-0.1867	-0.0483
2nd sub		0.1265	0.0192	-0.1141	-0.0223	0.3128	0.0397	-0.1834	-0.0388

Note: -3 to 1 means coefficients of dummy variables from third day prior the event on day 0 until the day after its occurrence. Total USDA: all WASDE projections, U.S. (World) positive: only WASDE U.S. (World) projections with change of stocks-to-use ratio > 0, U.S. (World) negative: only WASDE U.S. (World) projections with change of stocks-to-use ratio < 0, U.S. (World) big: only 80th percentile of the stocks-to-use ratio changes calculated with WASDE U.S. (World) projections, U.S. (World) small: only 20th percentile of the stocks-to-use ratio changes calculated with WASDE U.S. (World) projections. Coefficients of lagged returns are not reported. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Table 4a: Corn, futures prices reaction on CFTC publication of COT position changes (of hedgers and speculators)

Day to event	Total CFTC	Spec positive	Hedge positive	Spec negative	Hedge negative	Spec big	Hedge big	Spec small	Hedge small
Panel A: total sample (01/01/1996 – 6/30/2014)									
-3	0.0003	**0.0022*** **	**0.0021*** **	**-0.0013** **	**-0.0014** **	**0.0031*** **	**0.0029*** **	**-0.0022** **	**-0.0024*** **
-2	-0.0002	-0.0009	-0.0005	0.0003	0.0001	-0.0013	-0.0009	-0.0002	0.0003
-1	**-0.0008***	-0.0009	-0.0006	-0.0008	**-0.0010***	-0.0005	-0.0014	-0.0001	0.0002
0	**-0.0010** **	-0.0008	-0.0009	**-0.0011***	-0.0010	-0.0008	**-0.0016***	-0.0012	**-0.0017***
1	**-0.0007***	-0.0008	**-0.0015*** **	-0.0006	0.0001	-0.0019**	**-0.0024*** **	-0.0005	-0.0010
Panel B: 1st subperiod (01/01/1996 – 12/30/2005)									
-3	0.0002	**0.0020*** **	**0.0016** **	**-0.0012***	-0.0011	**0.0026*** **	**0.0023** **	**-0.0022** **	**-0.0021** **
-2	-0.0006	**-0.0018** **	**-0.0012***	0.0003	-0.0001	**-0.0022** **	-0.0013	-0.0002	0.0004
-1	**-0.0011** **	-0.0012	-0.0011	-0.0010	-0.0011	-0.0005	-0.0014	-0.0008	0.0005
0	**-0.0019*** **	**-0.0016** **	**-0.0019*** **	**-0.0020*** **	**-0.0018** **	-0.0012	-0.0017	**-0.0018***	**-0.0020** **
1	0.0005	-0.0010	**-0.0018*** **	-0.0001	0.0006	**-0.0016***	**-0.0034*** **	-0.0004	-0.0009
Panel C: 2nd subperiod (01/02/2006 – 6/30/2014)									
-3	0.0005	**0.0024** **	**0.0030*** **	-0.0015	**-0.0024*** **	**0.0043** **	**0.0044** **	-0.0024	**-0.0037***
-2	0.0006	0.0009	0.0009	0.0003	0.0003	0.0011	-0.0001	-0.0002	-0.0004
-1	-0.0002	-0.0002	0.0004	-0.0003	-0.0009	-0.0004	-0.0011	0.0031	-0.0011
0	0.0010	0.0006	0.0011	0.0014	0.0009	0.0003	-0.0013	0.0007	-0.0010
1	-0.0011	-0.0005	-0.0011	**-0.0017***	-0.0011	-0.0028	0.0006	-0.0001	-0.0014
Panel D: Average change of net positions									
total sample		0.0649	0.0232	-0.0582	-0.0231	0.1249	0.0447	-0.1151	-0.0430
1st sub		0.0878	0.0304	-0.0745	-0.0285	0.1430	0.0501	-0.1255	-0.0468
2nd sub		0.0404	0.0154	-0.0381	-0.0164	0.0894	0.0338	-0.0887	-0.0347

Note: -3 to 1 means coefficients of dummy variables from third day prior the event on day 0 until the day after its occurrence. Total CFTC: all CFTC publications, Spec (Hegde) positive: only those CFTC publications with a change of speculative (hedging) pressure > 0, Spec (Hegde) negative: only those CFTC publications with a change of speculative (hedging) pressure < 0, Spec (Hegde) big: only those CFTC publications with a change of speculative (hedging) pressure above the 80th percentile, Spec (Hegde) small: only those CFTC publications with a change of speculative (hedging) pressure lower than the 20th percentile. Coefficients of lagged returns are not reported. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Table 4b: Soybeans, futures prices reaction on CFTC publication of COT position changes (of hedgers and speculators)

Day to event	Total CFTC	Spec positive	Hedge positive	Spec negative	Hedge negative	Spec big	Hedge big	Spec small	Hedge small
Panel A: total sample (01/01/1996 – 6/30/2014)									
-3	**0.0008****	**0.0031*****	**0.0035*****	**-0.0014*****	**-0.0018*****	**0.0037*****	**0.0041*****	**-0.0025*****	**-0.0030*****
-2	0.0004	0.0007	0.0007	0.0001	0.0001	0.0009	0.0012	-0.0005	-0.0009
-1	0.0001	0.0003	0.0002	-0.0001	0.0001	0.0007	0.0004	-0.0013	-0.0003
0	-0.0001	0.0005	0.0005	-0.0006	-0.0006	0.0011	0.0006	-0.0001	-0.0005
1	0.0001	-0.0001	-0.0002	0.0002	0.0004	< -0.0001	-0.0005	0.0009	0.0009
Panel B: 1st subperiod (01/01/1996 – 12/30/2005)									
-3	**0.0008***	**0.0037*****	**0.00042*****	**-0.0019*****	**-0.0022*****	**0.0050*****	**0.0045*****	**-0.0035*****	**-0.0039*****
-2	0.0001	0.0002	0.0005	-0.0002	-0.0004	0.0011	0.0010	-0.0004	-0.0005
-1	-0.0006	0.0004	0.0001	**-0.0015****	-0.0012	0.0009	0.0003	**-0.0023****	-0.0005
0	-0.0006	-0.0001	-0.0003	-0.0010	-0.0009	0.0007	0.0003	-0.0003	-0.0010
1	-0.0001	-0.0002	0.0001	0.0001	-0.0001	-0.0001	-0.0009	0.0007	0.0004
Panel C: 2nd subperiod (01/02/2006 – 6/30/2014)									
-3	0.0008	**0.0022*****	**0.0026*****	-0.0007	-0.0012	0.0010	**0.0033****	-0.0002	-0.0014
-2	0.0008	0.0013	0.0009	0.0003	0.0008	0.0004	0.0015	-0.0009	-0.0018
-1	**0.0011***	0.0002	0.0002	**0.0021****	**0.0022****	0.0004	0.0006	0.0015	-0.0001
0	0.0007	0.0014	**0.0015***	0.0001	-0.0002	0.0018	0.0013	0.0002	0.0004
1	0.0002	0.0001	-0.0006	0.0004	0.0011	-0.0001	0.0003	0.0012	0.0017
Panel D: Average change of net positions									
total sample		0.0627	0.0274	-0.0611	-0.0274	0.1196	0.0504	-0.1164	-0.0513
1st sub		0.0785	0.0329	-0.0777	-0.0330	0.1294	0.0530	-0.1297	-0.0561
2nd sub		0.0443	0.0211	-0.0421	-0.0209	0.0989	0.0451	-0.0897	-0.0430

Note: -3 to 1 means coefficients of dummy variables from third day prior the event on day 0 until the day after its occurrence. Total CFTC: all CFTC publications, Spec (Hegde) positive: only those CFTC publications with a change of speculative (hedging) pressure > 0, Spec (Hegde) negative: only those CFTC publications with a change of speculative (hedging) pressure < 0, Spec (Hegde) big: only those CFTC publications with a change of speculative (hedging) pressure above the 80th percentile, Spec (Hegde) small: only those CFTC publications with a change of speculative (hedging) pressure lower than the 20th percentile. Coefficients of lagged returns are not reported. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Table 4c: Wheat, futures prices reaction on CFTC publication of COT position changes (of hedgers and speculators)

Day to event	Total CFTC	Spec positive	Hedge positive	Spec negative	Hedge negative	Spec big	Hedge big	Spec small	Hedge small
Panel A: total sample (01/01/1996 – 6/30/2014)									
-3	-0.0007	**0.0020*** **	**0.0025*** **	**-0.0032*** **	**-0.0038*** **	**0.0033*** **	**0.0037*** **	**-0.0046*** **	**-0.0051*** **
-2	-0.0006	-0.0005	-0.0006	-0.0007	-0.0006	-0.0007	-0.0004	-0.0006	0.0004
-1	**-0.0014*** **	**-0.0012* **	**-0.0012* **	**-0.0015** **	**-0.0015** **	-0.0011	**-0.0018* **	-0.0010	**-0.0024** **
0	-0.0004	-0.0008	-0.0012	-0.0001	0.0003	-0.0013	**-0.0021** **	0.0006	0.0010
1	**-0.0010** **	**-0.0019*** **	-0.0011	-0.0002	-0.0009	-0.0009	-0.0006	-0.0001	-0.0008
Panel B: 1st subperiod (01/01/1996 – 12/30/2005)									
-3	-0.0008	**0.0016* **	**0.0021** **	**-0.0030*** **	**-0.0035*** **	**0.0028*** **	**0.0028** **	**-0.0043*** **	**-0.0046*** **
-2	-0.0009	-0.0006	-0.0006	-0.0011	-0.0011	-0.0010	-0.0011	-0.0010	-0.0003
-1	**-0.0016** **	**-0.0017* **	**-0.0017* **	**-0.0015* **	**-0.0016* **	-0.0018	-0.0019	-0.0011	**-0.0024** **
0	-0.0007	**-0.0016* **	**-0.0021** **	0.0002	0.0007	-0.0017	**-0.0027** **	0.0006	0.0011
1	-0.0005	**-0.0015* **	-0.0009	0.0003	-0.0002	-0.0015	-0.0006	0.0008	0.0008
Panel C: 2nd subperiod (01/02/2006 – 6/30/2014)									
-3	-0.0007	**0.0025** **	**0.0032*** **	**-0.0037*** **	**-0.0047*** **	**0.0051*** **	**0.0066*** **	**-0.0059** **	**-0.0074*** **
-2	-0.0001	-0.0005	-0.0007	0.0002	0.0004	0.0005	0.0021	0.0009	0.0019
-1	-0.0009	-0.0004	-0.0003	-0.0014	-0.0016	0.0023	-0.0010	-0.0004	-0.0028
0	<0.0001	0.0009	0.0006	-0.0007	-0.0005	0.0009	<0.0001	-0.0003	0.0002
1	**-0.0017** **	**-0.0025** **	-0.0015	-0.0010	-0.0020	0.0019	-0.0007	-0.0034	**-0.0058** **
Panel D: Average change of net positions									
total sample		0.0551	0.0307	-0.0543	-0.0312	0.1069	0.0596	-0.1051	-0.0592
1st sub		0.0761	0.0422	-0.0730	-0.0412	0.1205	0.0661	-0.1168	-0.0637
2nd sub		0.0319	0.0181	-0.0317	-0.0191	0.0724	0.0431	-0.0705	-0.0446

Note: -3 to 1 means coefficients of dummy variables from third day prior the event on day 0 until the day after its occurrence. Total CFTC: all CFTC publications, Spec (Hegde) positive: only those CFTC publications with a change of speculative (hedging) pressure > 0, Spec (Hegde) negative: only those CFTC publications with a change of speculative (hedging) pressure < 0, Spec (Hegde) big: only those CFTC publications with a change of speculative (hedging) pressure above the 80th percentile, Spec (Hegde) small: only those CFTC publications with a change of speculative (hedging) pressure lower than the 20th percentile. Coefficients of lagged returns are not reported. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Table 5: Index Investment report, means of Index Trader Positions from December 31, 2007 to April 1, 2014

Corn	Soybeans	Wheat
0.311	0.307	0.462

Note: Means of Index Trader are calculated as the number of net long positions divided by total open interest

Table 6: DCOT report, means of each traders' categories from June 6, 2006 to June 24, 2014

	PMPU	Money Manager	Swap Dealer	Other Reportables	Non Reportables
Corn	0.315	0.121	0.234	0.041	-0.081
Soybeans	0.352	0.164	0.218	0.027	-0.057
Wheat	0.274	0.010	0.344	-0.030	-0.051

Note: PMPU = producers/merchants/processors/users. For PMPU, the mean is computed by net short positions divided by open interest. For all other trader categories, the mean is calculated as net long positions divided by total open interest.

Table 7a: Distributed Lag Model, monthly futures returns regressed on contemporaneous and lagged changes in stocks-to-use ratios from U.S. and world projections

	Corn		Soybeans		Wheat	
	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
Panel A: Futures returns on changes in stocks-to-use ratio from US projections						
	total sample (January 1996 – December 2014)					
U.S.	-0.161***	-6.30	-0.084***	-4.23	-0.081***	-2.63
U.S.(-1)	-0.004	-0.15	-0.008	-0.39	-0.005	-0.16
Adj. R^2	0.15		0.07		0.02	
	1st subperiod (January 1996 – December 2005)					
U.S.	-0.120***	-3.28	-0.102***	-3.99	-0.082**	-2.30
U.S.(-1)	-0.009	-0.24	-0.034	-1.25	0.025	0.69
Adj. R^2	0.09		0.11		0.04	
	2nd subperiod (January 2006 – December 2014)					
U.S.	-0.182***	-4.98	-0.066**	-2.11	-0.081***	-2.63
U.S.(-1)	-0.005	-0.13	0.017	0.52	-0.005	-0.16
Adj. R^2	0.18		0.02		0.02	
Panel B: Futures returns on changes in stocks-to-use ratio from world projections						
	total sample (January 1996 – December 2014)					
World	-0.456***	-6.12	-0.361***	-5.43	-0.339**	-2.53
World(-1)	0.015	0.189	-0.032	-0.46	-0.172	-1.27
Adj. R^2	0.15		0.11		0.02	
	1st subperiod (January 1996 – December 2005)					
World	-0.348***	-4.49	-0.331***	-4.49	-0.240*	-1.92
World(-1)	0.026	0.32	-0.006	-0.08	-0.136	-1.08
Adj. R^2	0.15		0.13		0.04	
	2nd subperiod (January 2006 – June 2014)					
World	-0.618***	-4.32	-0.424***	-3.09	-0.681*	-1.97
World(-1)	-0.003	-0.02	-0.091	-0.63	-0.264	-0.75
Adj. R^2	0.14		0.07		0.03	

Note: U.S.: coefficients of contemporaneous changes in the stocks-to-use ratio from U.S. projections, U.S.(-1): coefficients of lagged changes in the stocks-to-use ratio from U.S. projections, World: coefficients of contemporaneous changes in the stocks-to-use ratio from world projections, World(-1): coefficients of lagged changes in the stocks-to-use ratio from world projections. Coefficients of lagged returns are not reported. OLS with Newey-West standard errors. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Table 7b: Distributed Lag Model, weekly futures returns regressed on changes in trading pressure from hedgers and speculators

	Corn		Soybeans		Wheat	
	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
Panel A: Futures returns on change in hedging pressure						
	total sample (01/01/1996 – 6/30/2014)					
Hedge	0.709***	15.83	0.547***	20.09	0.510***	16.86
Hedge(-1)	-0.119***	-3.32	-0.031	-0.99	-0.070**	-2.54
Adj. R^2	0.35		0.36		0.28	
	1st subperiod (01/01/1996 – 12/30/2005)					
Hedge	0.563***	15.96	0.474***	17.21	0.420***	17.05
Hedge(-1)	-0.092**	-2.35	0.004	0.10	-0.066**	-2.29
Adj. R^2	0.50		0.43		0.43	
	2nd subperiod (01/02/2006 – 6/30/2014)					
Hedge	1.340***	12.86	0.761***	12.93	0.997***	9.83
Hedge(-1)	-0.233***	-2.97	-0.115**	-2.08	0.020	0.22
Adj. R^2	0.36		0.34		0.28	
Panel B: Futures returns on change in speculative pressure						
	total sample (01/01/1996 – 6/30/2014)					
Spec	0.214***	12.64	0.183***	14.80	0.263***	15.38
Spec(-1)	-0.043***	-3.79	0.005	0.35	-0.045***	-3.02
Adj. R^2	0.25		0.23		0.25	
	1st subperiod (01/01/1996 – 12/30/2005)					
Spec	0.173***	12.40	0.165***	12.56	0.217***	15.71
Spec(-1)	-0.027	-2.28	0.008	0.49	-0.042***	-2.59
Adj. R^2	0.38		0.31		0.40	
	2nd subperiod (01/02/2006 – 6/30/2014)					
Spec	0.442***	9.79	0.256***	10.29	0.610***	11.64
Spec(-1)	-0.076**	-2.53	0.009	0.34	0.047	0.86
Adj. R^2	0.26		0.17		0.28	

Note: Hedge: coefficients of contemporaneous changes in hedging pressure, Hedge(-1): coefficients from lagged changes in hedging pressure, Spec: coefficients of contemporaneous changes in speculative pressure, Spec(-1): coefficients from lagged changes in speculative pressure. Coefficients of lagged returns are not reported. OLS with Newey-West standard errors. ***, **, * denote significance at 1%, 5%, and 10% level, respectively.

Table A.1: WASDE-Data (±5 days around event day) on futures returns

		Corn	Soybeans	Wheat
All	All	-	2D*(+), 1D**(+)	1D**(+) D0***(-)
	Pre2006	D0***(-)	2D*(+), 1D*(+)	D0*(-)
	Post2006	D0**(+)	D0*(+)	D0***(-) D3**(-)
U.S. positive	All	D0***(-)	D0***(-)	D0***(-)
	Pre2006	D0***(-)	2D**(-), 1D***(-)	D0***(-)
	Post2006	D1**(-)	4D**(-) D0*(-)	1D*(+) D0***(-) D3**(-)
World positive	All	3D**(-) D0***(-) D4*(-)	1D*(+) D0***(-)	3D*(-) D0***(-)
	Pre2006	3D*(-) D0***(-)	4D**(+), 3D**(+) D0***(-)	D0***(-) D5*(+)
	Post2006	D0***(-) D3***(-)	4D***(-) 1D*(+)	3D**(-) **D0***(-)** D1**(-), D3***(-)
U.S. negative	All	1D**(+) D0***(+)	2D***(+), 1D***(+) D0**(+)	1D*(+)
	Pre2006	D0***(+)	2D**(+), 1D***(+)	D4*(-)
	Post2006	1D**(+) D0***(+)	2D**(+) D0**(+)	D5*(+)
World negative	All	5D*(+), 4D*(+) 3D**(+),1D*(+), D0***(+)	D0***(+)	3D**(+), 2D**(+), 1D***(+)
	Pre2006	4D*(+), 3D***(+) D0**(+)	1D*(+) D0**(+) D1**(+)	3D**(+), 1D**(+)
	Post2006	1D*(+) **D0***(+)**	D0**(+)	2D*(+), 1D**(+) D5***(+)
U.S. big	All	**D0***(-)** D3*(-)	D0*(-) D3*(-)	5D*(+) D0***(-)
	Pre2006	**D0***(-)** D1*(+)	-	1D*(-) D0**(-)
	Post2006	D0*(-) D3**(-)	4D**(-), 3D***(-) D0*(-)	1D**(+) D0***(-) D3**(-), D5*(-)
World big	All	D0***(-) D1**(+)	4D*(-) D0***(-)	D0***(-)
	Pre2006	D0***(-) D1*(+)	**D0***(-)**	D0*(-)
	Post2006	**D3***(-)**	4D**(-)	**5D**(+)** **D0**(-)** **D3***(-)**
U.S. small	All	2D***(+), 1D***(+) ***D0***(+)*** D1***(+), D2*(+)	2D*(+), 1D*(+) **D0***(+)**	1D*(+) D0**(+)
	Pre2006	2D***(+) D0***(+) D1**(+),D2**(+)	1D**(+) **D0***(+)**	3D*(+) D0**(+)
	Post2006	1D*(+) ***D0***(+)***	4D*(-) D0***(+)	-
World small	All	2D**(+) **D0***(+)**	2D*(+)	2D*(+),1D***(+)
	Pre2006	D0***(+) D1*(+)	-	4D**(+), 3D*(+) 1D***(+)
	Post2006	**2D*(+)**, 1D**(+) ***D0***(+)***	4D**(+)	D4*(+) **D5***(+)**

Note: XD = X days before the event; D0 = event day; DX = X days after the event. For significant coefficients: sign of significance in parentheses; **bold** if significant and coefficient > 0,01; ***bold and italics***, if significant and coefficient > 0,02. ***, **, * denote significance at 1%, 5%, and 10% level, respectively

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Traders' Motivation and Hedging Pressure in Commodity Futures Markets

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Working Paper

Abstract

This study seeks to elucidate major drivers behind participants' trading position changes and subsequently addresses the effect of interactions among traders on prices of commodity markets. We find that influential traders (managed money funds) not only are poised to follow price momentum in grains, softs, and meat commodities, they concurrently learn from hedgers' positions. We additionally find that some noticeable divergence among selected commodities in terms of trading directions results from changes of major fundamentals in the U.S. equity and bond markets and the behavior of the U.S. dollar. Results support our conjecture that there is a subtle contemporaneous feedback exerted by hedgers' positions on the positions of swap dealers and non-reportable traders. Furthermore, evidence per commodity reveals that on average commodity returns are profoundly influenced by positions of two groups of traders—hedgers and managed money funds, given the latter's larger size and informational advantage. Our evidence suggests that net traders' positions constitute the most important information channel via which market fundamentals influence commodity prices.

Keywords: Hedgers; Speculators; Market Participants; Motivation; Interaction; Trading Positions; Flight to Quality; Futures Prices; Commodity Markets.

JEL classification: C58, E44, F39, G11, G12, G13, G14, G15, G29, Q02.

1 Introduction

While the economics of commodity markets have received a considerable amount of recent research attention, some important unanswered questions remain, notably those related to the theoretical and empirical examination of drivers and motivators of various market participants. The behavior of many of these participants is the subject of continuing debate on the effects of trading, especially by speculators, and the recent Commodity Futures Trading Commission (CFTC) regulatory initiatives to possibly restrain such trades.

In this empirical study, we contribute to a debate prompted by concerns about the focus of speculators and their informational advantage over other market participants. We are motivated by some past studies that examined the determinants of hedging in futures markets (Hirshleifer, 1989; Rouwenhorst and Tang, 2012). Moskowitz et al. (2012) show that speculators follow time-series momentum strategies in many markets and profit from momentum returns at the expense of hedgers. Other work that highlights the role of speculators given the recent interest in commodities includes Büyükşahin and Harris (2011), Tang and Xiong (2012), Fattouh et al. (2012), Cheng et al. (2014), and Sockin and Xiong (2015).

Our objective is in line with and encouraged by the publication of a number of recent studies that attempt to examine financial issues within specific markets or a group of industries to gain insights that *would not* be possible once we amalgamate all the assets and ignore those specific factors. Studies with industry specifics are able to capture additional intuitions, as we intend to do in this study (see e.g. Hu and Xiong, 2013; Acharya et al., 2013). The present study examines two research questions: What is the impact of the financial fundamentals (equity, bond, and the US dollar) including momentum on trading position changes? Subsequently, what is the additional contribution and impact of changes in trading positions including hedging pressure on commodity prices? Ultimately, the answers to the proposed research questions are complementary and vital to our collective understanding about the economics of commodity markets, since drivers and forces behind the changes of trading positions subsequently impact commodity prices in futures markets via the trading activity channel. In our effort to understand these main drivers, our empirical examination tries to highlight the role of various types of traders given the predicament that each group of traders differs in their strategies, expectations, and motivation (Fuertes et al., 2015; Miffre and Rallis, 2007; Alexander et al., 2007).

Trading activities offer valuable insights regarding the commodity prices. Thus, we use various trading position measures computed based on the weekly Disaggregated Commitments of Traders (DCOT) of the U.S. Commodity Futures Trading Commission (CFTC) reports to test proposed hypotheses and examine the drivers behind the change of hedging pressure (hedgers' net short positions) and other traders' net long positions, and to successively examine impacts of trading activities of all CFTC participants (comprising the most influential traders, as they hold equal or above positions at the CFTC reporting level) on the price dynamic of a selected commodity. As empirical evidence speaks against an influence of index traders on commodity prices (Stoll and Whaley, 2010; Sanders and Irwin, 2010; Irwin and Sanders, 2012), we concentrate on the categories from the DCOT report. We analyze which market participants channeled financial factors in their trading strategies that led to an intensified co-movement with financial markets as observed in several studies (Tang and Xiong, 2012; Silvennoinen and Thorp, 2013; Delatte and Lopez, 2013; Büyükşahin and Robe, 2014). We then show results that differ across 22 commodities selected from five groups (energies, metals, grains, food and fiber (softs), and livestock and meats).

To our knowledge, no past studies have examined comprehensively the motivation behind trading activities of the CFTC traders per commodity or provided an empirical procedure to capture interactive effects among participants' positions and their influence on commodity returns. Our paper thus indirectly connects two strands of the literature. The first focuses on the trading activity and its impacts on asset pricing, as we intend to show the relevance of the trading behavior of participants in the prediction of the commodity returns and how it is linked to fundamental understandings (e.g. Fama and French, 1987; Erb and Harvey, 2006; Alexander et al., 2007; Miffre and Rallis, 2007; Büyükşahin and Harris, 2011; Gorton et al., 2012), in line with the substantial evidence that fundamentals can forecast stock market returns (see, for example, Chen et al., 1986; Keim and Stambaugh, 1986; Campbell and Shiller, 1988; Fama and French, 1988). The second strand of research addresses investment strategies of various participants in the commodity markets, notably trading strategies of sophisticated traders such as hedgers and speculators (e.g. De Roon et al., 2000; Fung and Hsieh, 2001; Sanders et al., 2004; Kaniel et al., 2008; Moskowitz et al., 2012; Rouwenhorst and Tang, 2012; Cheng and Xiong, 2014; Fuertes et al., 2015).

The rest of this paper is structured as follows: The next (second) section discusses key related studies to show the basis of our exploratory research questions. The third section looks at the data-collection methods, outlines the variables we use, and puts forth the preliminary analysis. The fourth section details the econometric methodology and models. The fifth section presents empirical evidence by looking more closely at determinants and motivation behind various trading positions in commodity markets and how interactions among participants influence the movement of commodity prices. Finally, the sixth section presents the conclusion and implications.

2 Related studies and hypotheses

The work of Singleton (2014) and Sockin and Xiong (2015) has raised some relevant questions about the existence of informational frictions in commodity markets. If the boom and bust of commodity of 2007–2008 is not isolated from the economic fundamentals, then we argue that traders' positions and trading activities of some participants should reveal valuable insights—notably in relation to the drivers behind their trading activities. Furthermore, we are interested in the interactions and learning effects induced by informational frictions among these participants and how such effects determine the movement of the commodity prices while controlling for the dynamic of equity markets (domestic and global), bond markets (domestic and global), and the U.S. dollar behavior. To understand major drivers behind the movement of the trading positions of five types of traders (hedgers, money managers, swap dealers, other reportables, and non-reportables) and in line with the work of Kang et al. (2014), we use a broad sample of selected commodities to include three energies contracts (crude oil, gasoline, and heating oil), three meats (lean hogs, live cattle, and feeder cattle), five metals (platinum, silver, gold, high-grade copper, and palladium), six grains (CBOT wheat, KCBT wheat, Spring wheat (MGEX), corn, soybeans, and oats), and five softs (cocoa, coffee, orange juice, sugar, and cotton).

Under market-linkage theory (e.g. Büyükşahin and Robe, 2014), we propose that the main drivers (motivators) behind the changes of position of all participants are 1) changes originating in the equity market or bond market for traders as they search for diversification benefits, or 2) the motivator is simply flight-to-quality during a crisis period that may manifest in trading position changes. Yet, we deem that other participants can revise their trading positions as a result of change of the U.S. dollar versus other major currencies; thus we suggest that the direction of the dollar does have a legitimate impact on the overall longer-term direction of commodities in general, as some past studies have shown in the case of energy or metals commodities (see, e.g., Sherman, 1982; Gisser and Goodwin, 1986; Jaffe, 1989; Johnson and Soenen, 1997; Draper and Faff, 2006; Nandha and Faff, 2008; Batten et al., 2010; Souček, 2013). In the present work we seek to examine to what extent the behavior of the U.S. dollar can be qualified as one of the factors that trigger some participants to buy or sell on any given day.[1]

For instance, Batten et al. (2010) find that monetary variables impact return volatilities of spot prices of gold, palladium, and platinum metals while also showing that equity market movements of both the U.S. and World have a sizeable effect on volatilities of platinum and palladium. In the same vein other studies have explored additional aspects of the behavior of stock market and commodity prices. Aruga and Managi (2011) show the causality between the U.S. and Japanese platinum and palladium futures markets such that the U.S. market leads the price to transmit information between both markets (see also Wang, 2001; Xu and Fung, 2005). De Long et al. (1990) show that rational speculators have a role in destabilizing market prices by triggering trend followers to trade when the prices move up. In addition, Mayer (2009) discloses that positions of experienced speculators tend to be replicated by other traders who are less informed—that is, small traders may have profit incentive to learn from sophisticated traders and thus to add to the intensity of speculators' positions.

We aim to extend understanding of the nature of the dynamic relationships among commodity participants. Building on past studies (e.g. Mork, 1994; Huang et al., 1996; Hamilton and Herrera, 2004; Rzepczynski et al., 2004), we advance the following hypotheses and then examine the impact of various financial fundamentals/variables including equity, bond, and past returns on the position of commodity traders.

Hypothesis 1A (H1A): *There is significant impact of financial fundamentals on trading activities of various participants in selected commodity futures.*

[1] Recently Olson, Vivian, & Wohar (2014) argued that past studies tend to ignore the importance of currency movements and their impact on the energy-equity relationship.

In our effort to explore what motivates different traders to change their positions, we seek to determine whether the dynamics in the big three markets—equity, bond, and the U.S. dollar (currency) markets—affect those positions. In other words, we hope to elucidate the contributions of *some* financial fundamentals to movements in trading activity of commodity participants. The fact that we are using a set of different commodities from various groups (from energies to metals, grains and meats) allows us to surmise the commonalities and distinctions among *all* types of traders across these groups—hedgers (HP), managed money (MM), Swap Dealers (SW), Other Reportables (OR), and Non-Reportables (NR). Yet contrary to some past studies that utilized an aggregate approach by amalgamating and pooling all commodity groups (all grains and metals, etc.) in order to test their propositions, we are purposely testing our hypotheses using individual commodities since not all commodities have the same level of participation (low to high liquidity). Furthermore, differences do exist within each commodity group and across all commodities, from those that are well-traded (e.g. crude oil) to those that are less frequently traded (such as oats). Therefore, we did not want to *mask* our results by providing an erroneous conclusion that might result from the aggregation approach or *ignore* the value of exploring some valuable insights into the dynamics of various traders that may exist within or across commodity groups.

Additionally, since we examine the effect of financial fundamentals, as outlined in H1A, on positions of participants in selected individual commodities, the following hypothesis—complementary in nature—focuses on differences among various commodity groups (e.g. energy vs. softs) and whether the effect of various financial variables is homogenous across all commodities. For instance, we anticipate divulging whether money managers tend to be momentum traders on every commodity or whether they have additional informational advantage in trading some commodities over others, and how they position their trading activities vis-à-vis the movement of the financial fundamentals (e.g. equity, bond, currency markets). Thus, we advance the hypothesis:

Hypothesis 1B (H1B): *There is a significant difference in positions among individual commodity futures; that is, the participants in various individual commodity futures position their trades differently as a result of changes in financial fundamentals.*

Our second research question concerning how changes of positions of traders and interactions among them impact commodity prices is based in part on the market microstructure literature and on the recent theoretical model of Sockin and Xiong

(2015), which proposes an extension of their basic equilibrium model while taking into account the informational frictions and incorporating a futures market. The authors suggest a realistic setting to highlight the role of informational noise by futures market trading, which affects commodity demand and spot prices. They propose in the timeline of the extended model that the three main traders (producers-long future, suppliers-short futures, and financial traders-long/short futures) in futures markets build their positions at time $t=0$ and choose to revise and unwind their positions before delivery at time $t=1$. In our empirical framework, to align with those authors' notations, the producers and suppliers are presented as hedgers, while the financial traders in this study are represented by four other types of investor (MM, SW, OR, and NR). Sockin and Xiong (2015) assume that the learning effect takes place with one-period time lag and underline interactive phenomena between suppliers and producers such that producers observe the private signals about global productivity at time zero, yet commodity suppliers observe that signal at time $t=1$. The proposed trading structure leads to two rounds of information aggregation, the first in the futures markets with informational noise originating from the activity of financial traders, and the second round of trading in the spot market when the financial traders unwind their futures positions and commodity suppliers (hedgers) observe a supply shock. In this context, the interaction among major influential traders is established; thus we forestall highlighting the nature, direction, and type of interactions among all agents (e.g. hedgers and managed money traders).

Sockin and Xiong (2015) suggest using a multiplicative term that represents the *contribution* of financial traders in the aggregate position of producers such that the two components of this term capture (1) *knowledge* of financial traders about the global fundamentals and (2) *trading activities* not related to the fundamental(s) but instead manifested by diversification motives that are *unobserved* by other market participants. In that sense, we argue that changes of positions of main traders beyond global fundamental determinants assist in revealing the nature of direct impact on commodity prices, and at a minimum this new interactive channel among traders should increase questions about the relevance of informational advantage and contemporaneous learning among participants.

In their theoretical models, Sockin and Xiong (2015) show that activity of financial traders does not have a *direct* impact on commodity supply and demand, yet it does affect the futures price, which can *indirectly* impact commodity demand and the spot price. Through the projected influence of financial traders, Sockin and Xiong (2015) show that traders in commodity markets (financial traders) can exert an impact on those markets via the informational feedback channel—originating from the unobservability of the positions of different participants—of commodity futures prices. While Sockin and Xiong (2015) reiterate and call for more complete empirical models that consider informational frictions in trading activities of participants, the present study seeks to examine the interactions between various participants and to investigate how relevant positions of some participants influence the positions of other traders. Thus we indirectly respond to concerns about how commodity prices impact agents' expectations. In our study, we try to tackle the contemporaneous feedback and interaction among traders given the high correlation between positions of hedgers and speculators by following a two-step statistical procedure as presented in Bosch and Pradkhan (2015).

In line with the study of De Roon et al. (2000) that examines the cross-hedging properties of the commodity markets, we anticipate evidence of this cross-market linkage in relation to the interaction between trader types. Thus the following hypothesis examines how the position changes of different trader groups impact the pricing of the commodity. As is documented based on the informational arguments, some traders will follow the strategy of the most influential participants, while in other instances traders may adopt a contrarian strategy, which may depend on the nature of the commodity.

Hypothesis 2: *The dynamic interaction among influential commodity participants exerts a significant impact on commodity prices.*

While hypotheses H1A and H1B anticipate the main drivers behind the positions of commodity participants, in hypothesis 2 we are subsequently more concerned with how the changes of these positions of different traders impact the pricing of the commodity.

3 Data

For the empirical analysis we use weekly data from June 13, 2006 to December 30, 2014 of the positions from the Disaggregated Commitments of Trader (DCOT) report and 22 selected commodity futures contracts. Futures contracts are included only when the DCOT data are available from the beginning date of June 13, 2006:

Energy: WTI Crude Oil (NYMEX), Heating Oil (NYMEX), RBOB Gasoline (NYMEX)

Metals: Gold (COMEX), Silver (COMEX), Platinum (NYMEX), Palladium (NYMEX), Copper (COMEX)

Grains: Soft Red Winter Wheat (CBOT), Hard Red Winter Wheat (since end of 2013 CBOT, formerly KCBOT), Hard Red Spring Wheat (MGEX), Corn (CBOT), Soybeans (CBOT), Oats (CBOT)

Softs: Cotton (since September 2007 ICE, formerly NYBOT), Orange Juice (ICE), Cocoa (since September 2007 ICE, formerly NYBOT), Sugar (since September 2007 ICE, formerly NYBOT), Coffee (since September 2007 ICE, formerly NYBOT)

Livestock: Lean Hogs (CME), Live Cattle (CME), Feeder Cattle (CME)

Data on futures prices are from Datastream. To construct a continuous return series, contracts are rolled over based on the open interest. As long as the first-nearby contract shows the highest open interest, returns are calculated from the first-nearby contract. When the open interest of the second-nearby contract exceeds the open interest of the first-nearby contract, the rollover takes place and returns are calculated by the second-nearby contract. This methodology is also applied by Brunetti and Büyüksahin (2009). It is the best approach when analyzing trader positions and the relation to futures returns, since data on trader positions are based on all open positions. Thus, the impact of traders' positions will be best reflected in the contract where the largest part of all traders is invested. For instance, Carchano and Pardo (2009) note that traders prefer open interest as an indicator of liquidity, instead of volume, in order to switch contracts in liquidity peaks.

Positions data of the DCOT report are collected by the CFTC every Tuesday and provided to the public the following Friday. Next we present the description of the five trader categories of the DCOT report as listed in the CFTC's explanatory notes and include some literature on findings about trader behavior:

Producers/merchants/processors/users (HP) are physical traders that trade on futures markets to manage or hedge risks arising from their activity in the physical commodity business. Kang et al. (2014) show that hedgers trade as contrarians and that they provide liquidity to speculators; and Mutafoglu et al. (2012) find that hedgers are negative feedback traders in precious metals markets—they sell when prices rise.

Managed money traders (MM) are non-commercial traders which include registered commodity trading advisors (CTA), registered commodity pool operators (CPO), and unregistered funds like hedge funds, floor brokers, and traders. They trade in commodity markets on behalf of their clients. The MM traders are another group that is often examined in the literature, and they are usually regarded as traditional or professional speculators, often associated with trend-following behavior (e.g. Borin and Di Nino, 2012; Baltas and Kosowski, 2013; Hutchinson and O'Brian, 2014) and a short-term orientation (e.g. UNCTAD, 2011; Tokic, 2012).

Swap dealers (SW) trade on futures markets solely to hedge and manage risks arising from their swap transactions. The clients of SW can be traders who trade for speculative or hedging purposes, thus it is difficult to identify the initial motivation of the clients to enter into a swap contract with SW. Brunetti and Büyüksahin (2009) use the SW category to proxy index traders for the energy and the corn futures markets. While data on the positions of index traders are directly available by Index Investment Data (IID), the limitations of IID prevent usage in many studies. IID is available on a monthly basis, and before June 30, 2010, only on a quarterly basis. Irwin and Sanders (2012) show that for energy and metals futures markets, the SW category is a poor proxy for index traders' activity, while for agricultural markets high correlations between SW and index traders indicate a close match of the two trader categories.

Other reportable traders (OR) are obliged to report their positions but do not fit in any of the three mentioned trader categories. Tokic (2012) finds for the crude oil market that OR trading activity is determined by fundamental analysis.

Non-reportable traders (NR) are not described in detail in the explanatory notes of the CFTC; they are the part of all open positions not covered by the four reporting trader categories due to the number of positions they hold. Only when a trader exceeds a specified level of positions held by one trader is he or she obliged to report positions to the CFTC. Because NR traders are not defined in detail by the CFTC, the motivation of a single NR trader to trade in a commodity futures market might be speculation, hedging, or portfolio diversification.

The CFTC emphasizes that the trader categories cannot be interpreted as a detailed description of the corresponding trading activities. Thus, the description in the explanatory notes of the CFTC leaves a lot of latitude for how the different categories actually behave in futures markets. Several attempts were made to analyze the behavior or the impact of different trader categories on commodity prices and/or volatility, with most weight on index traders (either IID or proxied by SW) and the speculative traders (MM or non-commercials).[2] But very few studies analyze all trader categories' behavior and the impact of their interaction on all of those commodity markets for which the DCOT report is available.[3]

4 Econometric Methodology

Preliminary analysis

Table 1a presents the summary statistics of futures returns and traders' position *changes* based on the selected commodities over the sample period (weekly data from June 13, 2006 to December 30, 2014). For hedgers, we calculate the net short positions similarly to De Roon et al. (2000), where it is defined as hedging pressure (HP). While those authors divide the net short positions of hedgers by hedgers' total positions, we are interested in the relative importance of hedging pressure and therefore divide by total open interest:

$$HP_t = \frac{Short\ positions_t - Long\ positions_t}{Open\ interest_t} \quad (1).$$

To ensure stationarity net short position changes of hedgers are calculated as absolute changes:

$$\Delta HP_t = HP_t - HP_{t-1}. \quad (2).$$

For all other traders' net long positions are calculated as:

$$pos_{t,i} = \frac{Long\ positions_{t,i} - Short\ positions_{t,i}}{Open\ interest_t}, \quad (3).$$

$with\ i = MM, SW, OR, and\ NR$

[2] Before the introduction of the DCOT Report on October 20, 2009, data of the Commitments of Trader Report (COT) were used in studies analyzing the behavior or impact of traders in futures markets. The COT divided all traders into commercials and non-commercials. Commercials trade for hedging purposes, and non-commercials are typically associated with speculative behavior.

[3] Tokic (2012) takes all trader categories into account. However, his findings are solely based on a graphical analysis of the positions on the crude oil futures market.

To ensure stationarity net long position changes of all other traders are calculated as absolute changes:

$$\Delta pos_{t,i} = pos_{t,i} - pos_{t-1,i} \quad (4).$$

We note that the mean returns of energy commodities are negative with varying signs in the case of other commodities (metals, grains, soft, and meats), highlighting the observation that not all selected commodities behave in the same fashion. Instead there is a great mixture of returns within the commodity market. In addition, we note that on average hedgers have slightly decreased their net short positions in 12 out of 22 commodities during the sample period, while the other reportable (OR) traders have shown an increase of their net long positions on a weekly basis by 1.8% in silver. The standard deviation of net positions of all five types of traders shows diversity of trading positions such that a high standard deviation implies higher tendency of a group of traders to change their net positions frequently, and this group may be considered a market mover due to its size and informational advantage. Results in Table 1a show that among traders, managed money funds (MM) tend to showcase at, or near, the high end of the possible standard deviation range with respect to energy, metals, livestock, and meats futures markets (1.18% to 4.76%); thus they have a tendency to trade and change their net long positions frequently in search of profitable opportunities or to reposition their investment strategies in light of anticipated pertinent market estimates and announcements. In grains, and in food and fiber markets, hedgers are the most active traders.

Because swap dealers (SW) are often associated with index trading and therefore rather passive long trading, the standard deviations of their net position changes are expected to be low. The replication of a commodity index does not require high frequent rebalancing. For all commodity markets, apart from metals markets, low standard deviations can actually be observed. The higher standard deviations of swap dealers' position changes in metals markets are near to those of hedgers. Therefore using swap dealers as a proxy for index traders with passive trading behavior would not be adequate for metals markets. OR and NR traders are the least active traders in almost all commodity futures markets.

In Table 1b, we calculate participants' propensity to trade (PT) per commodity based on the weekly data as a fraction of gross net positions:

$$PT_t = \frac{abs(long\ positions_t - long\ positions_{t-1}) + abs(short\ positions_t - short\ positions_{t-1})}{long\ positions_{t-1} + short\ positions_{t-1}} \quad (5).$$

Results show that the propensity to trade of MM and OR is higher in energies and grains. We note cases in our results where the PT of managed money funds is higher than that of the OR or SW traders in soybeans, gold, heating oil, and crude oil, which possibly supports the conjecture that OR traders adopt or follow similar trading strategies in some commodities as those of MM. Hedgers trade less actively by the PT measure. This was also expected, since hedgers use futures markets to manage risks, which can be achieved at lower frequencies. MM as professional speculators are expected to adjust their positions frequently in order to profit from any market movement. Compared to the standard deviations from the net positions, the values of the PT measure are quite high for OR and NR traders on most commodities. So while they do not seem to trade very actively by the values of their net long positions, the propensity to trade shows that they adjust their long and short positions, considered separately, quite frequently.

On the other hand, it is worth noting that other types of traders (SW, OR, and NR) exhibit various mean net positions across all selected commodities, a fact that grants support to the idea that trading strategies differ across various types of traders, and across all commodities; thus we cannot claim that all participants adopt the same positions even within the same group of commodities such as metals, grains, or livestock and meats (Table 1b). Hedgers are by far the most important player in the net short positions in all markets, apart from crude oil and feeder cattle. In the crude oil market some hedgers seem to manage their risks via swap dealers, since swap dealers are net short on average in crude oil. In feeder cattle markets the majority of hedging seems to be done by traders who are too small to be obliged to report, considering the high value of net short positions of NR traders and the very low share in net short positions of hedgers. MM share of net long position lies between 5 and 26 percent in most commodities.

SW mean net position shares of open interest on crude oil and precious metals except copper are negative; while on all other commodities their net positions' share is positive. SW have quite high participation in the net long positions for nearly all soft commodities, but these participants do not adjust their long and short positions as frequently as the PT measure indicates, except in Minneapolis wheat and feeder cattle.

However, it must be taken into account that SW in the Minneapolis wheat futures market have for several periods no open positions at all; therefore the PT measure is distorted by the large jumps from zero to a non-zero value.[4] The finding of Irwin and Sanders (2012) that for agricultural futures markets SW are an appropriate proxy for index traders thus is indirectly supported by our data, as the SW are on average long in their positions and trade passively on agricultural commodities.

To enhance our collective understanding about the relationship among various types of traders in the commodity markets based on our selected sample, we rely on the reflection gathered from correlation matrices of the four types of traders' positions per commodity. Table A.1 in the appendix shows correlation among traders' positions: we notice a high positive correlation between HP and MM traders' positions across all listed commodities, which echoes our prior observation that HP and MM are the main traders in the commodity markets, and both add to the liquidity of the commodity market since they accommodate and tend to trade against each other. However, evidence reveals that SW, OR, and NR positions do not exhibit a consistent correlation across all commodities. For instance, OR positions have a negative correlation with MM traders in orange juice, which implies that OR traders take a net long position in orange juice during the time period when MM are net short. Due to this high correlation coefficient between HP and MM, we decided to test our Hypothesis 2 and run the regression using a step-wise statistical procedure, as described in the next section.

Econometric methodology

Parallel with our hypotheses, our analysis concentrates on two primary questions. First, what drives the different traders in commodity futures markets? More specifically, is their trading determined by momentum or contrarian behavior, and do they show herding behavior? In addition to these drivers, we take into account the fact that traders' behavior might be determined by financial fundamentals. The data set of 22 commodities and five trader categories is broad enough to shed light on similarities in trading behavior in commodity groups and/or trader categories. The drivers of the trading behavior of hedgers are analyzed by the following regression:

[4] From June 13, 2006 to January 16, 2007, swap dealers (SW) have no open positions on the Minneapolis Grain Exchange (MGEX) at all. Plus, SW on MGEX rarely hold short positions during the full selected period. The specific dates when SW hold no long and short positions are: August 7-28, 2007; December 24, 2007, to January 21, 2008; February 12 to October 14, 2008; and February 3 to April 7, 2009.

$$\Delta HP_{t,i} = \alpha_i + \delta \Delta HP_{t-1,i} + \gamma_i r_{t-1,i} + \beta' X + \omega_i D_{FebBreak} + \varepsilon_t \quad (6).$$

with i for the 22 individual commodities. ΔHP_t is the change of hedgers' net short positions. A positive sign of the coefficient δ can be interpreted as persistence in the trading behavior. To account for the reaction of hedgers to past returns, the lagged returns r_{t-1} are included. A positive sign of γ indicates contrarian trading, and positive past returns are followed by hedgers building up net short positions. A negative sign would demonstrate that hedgers behave as momentum traders, reducing their net short positions after prices increase. The remaining factors, $X = \begin{pmatrix} \Delta DI_t \\ \Delta DI_{t-1} \\ \Delta EquityProxy_t \\ \Delta EquityProxy_{t-1} \\ \Delta BondProxy_t \\ \Delta BondProxy_{t-1} \\ \Delta VIX_t \\ \Delta VIX_{t-1} \end{pmatrix}$, account for the possibility that trading behavior is determined by macroeconomic and financial factors. ΔDI is the change of a U.S. dollar trade-weighted spot index. A weaker dollar is expected to increase the demand on commodities from non-U.S. countries, as all commodities are denominated in U.S. dollars. $\Delta EquityProxy$ is the return of the S&P 500 index, and $\Delta BondProxy$ the return of the World Government Bond Index (WGBI) for United States and all maturities. These two factors account for the possibility that traders' behavior is also driven by developments in financial markets.

As a robustness check, we alternate the equity and the bond proxy to account for developments in global financial markets. In the robustness check, we use the MSCI world index as the equity proxy and the WGBI world index "all maturities" as the bond market proxy instead of the U.S. equity and bond market proxies. ΔVIX is the change of the volatility index, which reflects the implied volatility of options on the S&P 500. It measures financial sentiment regarding market conditions and market uncertainty. As we want to concentrate on the short-term pricing of each commodity, we deem it is relevant to only include contemporaneous and one-week lagged factors in the regression. $D_{FebBreak}$ is a dummy for the month of February. It accounts for seasonality effects especially for grains, where in February new fundamental information leads traders to revise their strategies.

For all other trader categories, the regression is almost identical to the specification for hedgers in Equation (6), with the only difference being that a hedging pressure term is included:

$$\Delta pos_{t,i}^{j} = \alpha_i + \delta_i \Delta pos_{t-1,i}^{j} + \gamma_i r_{t-1,i} + \theta_i \Delta HP_{t,i} + \beta' X + \omega_i D_{FebBreak} + \varepsilon_{t,i} \qquad (7).$$

with i for the 22 individual commodities and j for the four trader categories MM, SW, OR, and NR. The reason for including hedging pressure here is to consider that members of the four trader categories might incorporate the behavior of hedgers in their trading strategy. One reason is that hedgers' behavior is expected to reflect some informational content about the fundamental state of the commodity, since hedgers use futures markets to hedge and manage risk arising from their business in the physical commodity (Sockin and Xiong, 2015). Another reason for market participants to follow hedging pressure is the finding of De Roon et al. (2000), who state that commodity futures returns can significantly be explained by hedging pressure. Conversely, it's possible to argue that we do not expect hedgers to follow other traders' strategies, since their main focus is to manage risk, which should not depend on the behavior of other market participants.

The second question in alignment with hypothesis 2 asks how interactions between the different traders impact pricing in commodity futures markets. As it is impossible to include all traders in one regression due to the high correlation between hedgers and managed money (Table A.1), the impact of interaction effects of the different market participants is investigated with a two-step procedure: We first separately regress the return of the individual commodity futures on hedgers or managed money net position changes. The control variables—which show at least for several commodities and traders' net position changes a significant influence in Equations (6) and (7)—are also included to explain the futures returns:

$$r_{t,i} = \alpha_i + \gamma_i r_{t-1,i} + \theta_1^{HP} \Delta HP_t + \theta_2^{HP} \Delta HP_{t-1} + \beta' X + \varepsilon_{t,i} \qquad (8a).$$

$$r_{t,i} = \alpha_i + \gamma_i r_{t-1,i} + \theta_1^{MM} \Delta MM_t + \theta_2^{MM} \Delta MM_{t-1} + \beta' X + \varepsilon_{t,i} \qquad (8b).$$

Then, the part ε_t—which cannot be explained by the control variables and hedgers according to Eq. (8a) or MM traders' net position changes as illustrated in Eq. (8b)—is tested on every other trader category's net position changes singly:

$$\varepsilon_{t,i} = \alpha + \delta_1 \Delta pos_{t,i}^j + \delta_2 \Delta pos_{t-1,i}^j + u_{t,i} \quad (9).$$

with j for each trader group not already included in Eq. (8a) or Eq. (8b). So, for example, the error terms of Eq. (8a), where hedgers are included, are tested singly by Equation (9) for MM, SW, OR, and NR. This is done by the contemporaneous and lagged relationship, in order to determine whether the part which cannot be explained by the control variables and hedgers or managed money is significantly related to the net position changes of other traders. Inclusion of the contemporaneous net position changes is not intended to help us find a direct impact of traders on commodity pricing or an influence of commodity pricing on traders' net position changes. The aim is to see whether the different trader categories play a role in the interaction of all trader categories that influence pricing of commodity futures. The lagged position changes of other trader categories in Equation (9) are included to examine whether the part which is not explained by Eq. (8a) or Eq. (8b) can be forecasted by positions of the different traders.

5 Empirical results

5.1 Motivation and determinants of trading positions in commodity futures

Table 2 presents HP (hedgers' net short position) results based on Equation (6) in alignment with hypothesis 1. Since we are concerned with identifying the main drivers behind the position changes of major CFTC traders *per commodity,* results depict the impact of the big four markets (currency–the U.S. dollar, equity, bond markets, and overall market uncertainty) as possible main drivers behind position changes. Among the five groups of commodities, we note that the dollar index movement has a statistically significant negative impact on HP except in the case of crude oil, cotton, live cattle, and lean hogs. Furthermore, hedgers in grains and softs except sugar, metals except gold, and meats are contrarian traders—not in all commodities, though, but in 16 out of 22—which implies that hedgers reverse their positions on prior performance of commodity in question in addition to their trading persistence in the majority of commodities. Yet, we cannot rule out that they are not merely influenced by price momentum of commodity or the U.S. dollar movement but also to a lesser extent by the U.S. equity and bond markets as proxied by the S&P 500 index and WGBI. Evidence shows that the net short positions of these hedgers are positively influenced by the equity market and negatively by the bond market. Weak results are observed from the proxy of extreme market condition; the implied volatility (VIX) has a positive effect on hedgers' net positions in heating oil, corn, and cocoa, but negative on hedging positions of crude oil, gasoline, palladium, and sugar.

February break is a seasonal phenomenon (weakness with commodities per se) specifically observed by traders and practitioners in commodity markets in grains and soft commodities as a time period when participants revise their trading strategies and prepare to be positioned in the commodity markets in light of new seasonal trends, inventory direction, and information. Historical daily data in grains show that in February, sharp increases and equally sharp breaks are not uncommon; as practitioners have noted, a weakness associated with the second month of the year is well known and anticipated. Thus, it is critical to our understanding to include this dummy variable to avoid capturing incorrect changes in trading positions that may be due to this usual seasonal variation, as some sophisticated traders prefer to be in the sidelines of some commodities during this period (seasonal effect changes) (see also, e.g., Ritter, 1988; Saunders, 1993; Hirshleifer and Shumway, 2003; Kamstra et al., (2003); Garrett et al., 2005; DeGennaro et al., 2008; Kamstra et al., 2014). Results in Table 2 support only 2 out of 22 cases when we find that hedgers' positions are positively influenced by this break (sugar, and crude oil).

On average, the explanatory power of the variables to describe the position changes of hedgers is lowest for energy and metals futures markets. It is especially low for the crude oil and the silver futures markets.

Along these lines, Table 3 addresses and tests the same hypothesis using the CFTC managed money (MM) net positions as the dependent variable. Given the fact that this group of traders do differ in their strategies, expectations, and motivation, it is essential to understand the main drivers behind the changes of their positions over the sample period. Evidence in Table 3 illustrates that as the U.S. dollar comes under downside pressure, the MM net positions improve in energy, gold, and spring wheat, but when the dollar is under upside pressure, the MM net positions increase for cocoa. Additionally, HP has a positive and statistically significant effect on MM net long positions across all selected commodities. This evidence supports the contemporaneous feedback between these traders in line with some past studies that examine traders' reaction and that of rational investors who may prefer to ride bubbles because of predictable investor sentiment (e.g. Brunnermeier and Nagel, 2004). MM net positions are less driven by persistent behavior compared to hedgers. Cases of momentum traders were observed in MM net positions, but returns of commodity in question are only significant when the traders' net positions are in crude oil, corn, CBOT wheat, spring wheat, oats, soft commodities, and meats.

The U.S. equity market performance has a smaller impact (contribution) on MM positions. Additionally, evidence reveals that an appreciation of the bond market has a tendency to encourage an increase of net long positions of MM in gold but also a dec-rease of their positions in crude oil, gasoline, platinum, and corn. Overall market conditions as proxied by implied volatility show that high uncertainty and sentiment exhibit a mixed effect on net positions of traders in few commodity futures markets. In contrast to hedgers' positions, February break shows a statistically significant (but not economically significant) effect on positions of heating oil, gold, palladium, corn, and CBOT wheat. Overall, we find that explanatory powers of our estimations are higher in Table 3 than those given in Table 2. This can be attributed to the high and significant values resulting from the inclusion of hedging pressure, which is supported by the high correlations between money managers and hedgers as presented in Table A.1.

In contrast to the MM traders, swap dealers (SW) reverse their positions (Table 4) when commodity returns of energy, copper, grains except soybeans and spring/winter wheat, softs except cocoa, and meats are declining. This observation shows that SW traders tend to trade as contrarians, and that the major driver/force behind the changes of position are the U.S. dollar and hedgers' positions (that is, when HP improve then the SW net long positions increase in crude oil, gasoline, grains, softs except cocoa, and meats). For the two precious metals gold and silver, SW negatively react to HP. This again confirms the different behavior of SW in the gold and silver markets. SW net long positions are very persistent, similar to HP. Contrary to results in Tables 2 and 3, the dollar index upside movement harkens an increase of SW positions in energies except gasoline, metals, spring wheat, cotton, and orange juice. Perhaps this result could be explained by a large portion of non-U.S traders or participants who can benefit from an increasing dollar channeled by commodity prices.

The U.S. equity market has minor negative effects on some SW positions in crude oil, orange juice, and sugar, with a positive impact on positions in cocoa and feeder cattle. The U.S. bond market movement is considered an important determinant of gold

SW positions such that when the bond market performs, SW have a tendency to lower their positions in gold, but they increase them in copper, corn, CBOT wheat, winter wheat, and orange juice. The implied volatility shows again a weak yet statistically significant impact on SW positions in heating oil, gold, copper, feeder cattle, and live cattle. At this stage we can deduce that increase of SW positions in gold is driven by an underperforming bond market and high market uncertainty, lending partial support to the "safe haven" argument.[5]

Table 5 presents results of net positions of the CFTC Other Reportables (OR). Positions of this group of participants are negatively influenced by commodity returns prior performance. In the cotton, orange juice, and sugar futures markets, there is some persistent behavior of the net long positions of OR. Alternatively, in the silver and palladium futures markets, past position changes are negatively related to the present ones. Hedgers' positions influence their trading strategies in a majority of cases (16 out of 22 selected commodities), yet the direction of their trading positions differs in some instances; they lower those positions in copper and CBOT wheat and increase them in crude oil, platinum, palladium, corn, soybeans, and meats. For OR, the financial variables play a minor role. A weaker tone in the U.S. dollar index was bearish for the net positions of this group of traders in copper but bullish in spring wheat, as it made the U.S. wheat more attractive to foreign buyers. Given such a scenario, OR traders are inclined to increase their positions. Both equity and bond markets have a mixed effect (negative or positive) on some of the selected commodities. In sum, positions of this group of traders are largely driven by hedgers' positions.

Table 6 presents results regarding the net long positions of the last group of traders, the non-reportables (NR). In energy markets and the palladium market, NR seem to be driven by momentum trading, while on the livestock and meat futures markets there is some weak evidence of contrarian trading. The big picture that emerges from Table 6 supports past observations that this group of traders (small traders) tends to follow and simultaneously learn from the hedgers' positions. We note that the U.S. dollar movement drives the NR traders' net positions in metals, soybeans, and softs expect orange juice. The U.S. stock market does not exert a consistent effect on their

[5] Joy (2011) examines the relationship between gold and the U.S. dollar using a dynamic model while trying to determine if gold acts as a hedge against the U.S. dollar or is a safe haven, or perhaps neither of these. Kaul and Sapp (2006) define a financial safe haven as "an ideal venue to park money during periods of uncertainty." A hedge asset is one that is on average uncorrelated or negatively correlated with another asset (see Baur and McDermott, 2010).

trade but has some effect in gasoline, gold, palladium, cocoa, and live cattle. Additionally, only 7 out of 22 commodity positions are influenced (positively or negatively) by movement of the U.S. bond market.

Based on Tables 4 to 6, we note that HP coefficients which are statistically significant tend to be smaller in magnitude—sometimes negative—than those presented in Table 3 (case of the MM positions), which brings our attention to a lower contemporaneous feedback that HP positions exert on the positions of these groups of traders (SW, OR, and NR). Contrary to the HP, MM, or SW, we notice that OR and NR traders tend to be less persistent in their trading strategies from one period to another, since we find cases when they reverse their positions (reduction or surge) per commodity; this implies that they are reluctant to hold the same positions over a longer term due to their low risk tolerance vis-à-vis the MM traders.

Furthermore, a negative coefficient of the prior commodity returns on the positions of these groups of traders shows that they tend to reverse their positions (reduce their positions) when commodity returns are higher because this matches their short-term focus to sell after a high performance of commodity return—they are gain seekers. Overall, we find similarities and differences in trading behavior among all types of traders, and given the predicament that fundamentals at least partly drive their positions, our contention *not* to amalgamate all commodities in our empirical approach is clearly supported, in line with some past studies. For instance, Erb and Harvey (2006) point out that commodity futures are not correlated with one another, proposing that to consider them a market of individual *unrelated* assets is more meaningful than to accept them as a homogenous market of similar assets.

The futures prices of commodities traded in the U.S. are frequently used as barometers of the global economy (see also, e,g., Gorton and Rouwenhorst, 2006; Erb and Harvey, 2006; Kilian, 2009; Kilian and Murphy, 2014; Singleton, 2014). This dependence on U.S. futures to forecast the global economy arose in part due to the global focus and reach of commodity markets, with various traders from multiple countries participating in the U.S. commodity market for diversification of their holdings (as documented in past studies, e.g., Hu and Xiong, 2013).

Thus, for purposes of robustness of our results and to examine the effect of the world equity and bond markets, in this section we repeat the previous estimations based on Equations (6) and (7), while including world equity market proxy of MSCI and the world bond market proxy of WGBI world (noted "the world approach") instead of the U.S. equity and bond markets' proxies. Results are given in the appendix, Tables A.2 to A.6, which represent the positions of hedgers, managed money, swap dealers, other reportables, and non-reportables, respectively. We find some noticeable *additional* statistically significant impact/contribution of the world equity—not found before when we used the U.S. equity—on hedgers' net positions, an impact that is negative in crude oil and positive in the palladium, copper, corn, spring wheat (MW), cotton, and coffee futures markets. In sum, the evidence does not differ qualitatively from the data presented using the U.S. equity and bond markets, notably for other types of traders (see Tables A.2-A.6 in the appendix).

5.2 Interaction and contemporaneous effects among commodities' participants

Main variables:

To examine price impact of various participants since their interactions are relevant in price determination, we examine the relationship between trading positions and futures returns of each trader type per commodity in alignment with hypothesis 2 and the microstructure literature (e.g. De Roon et al., 2000; Haigh et al., 2007; Büyükşahin and Harris, 2011; Hong and Yogo, 2012; Rouwenhorst and Tang, 2012; Acharya and Naqvi, 2012; Büyükşahin and Robe, 2014).

Based on the results presented in Table 7a (hedging pressure version) and Table 7b (managed money version), we notice that returns of selected commodities (energy, metals, grains, softs, and meats) except crude oil are all positively influenced by hedging pressure represented by the HP measure. Yet in Table 7b (managed money traders) we note that the change of MM position which proxies the speculative pressure has a higher and positive impact on the movement of futures returns across all selected commodities. In addition, the explanatory power in Table 7b is slightly higher than that of Table 7a, which possibly highlights the additional and important role of this group (MM) of traders on the behavior of commodity futures. Especially for crude oil, the explanatory power is nearly 30 percent higher for the regression with MM included. For soft commodities results are mixed. While orange juice, sugar, and meat returns are better described with MM, cotton is better described by hedging pressure. Grains except oats returns can be slightly better explained by the hedging pressure version of Equation 8a.

Furthermore, the majority of coefficients of both the lagged HP positions in Table 7a and the lagged MM positions in Table 7b tend to be negative, an observation that supports the liquidity argument as price of the commodity in question makes necessary corrections and reversal of prices occurs after an excessive trading period. Nevertheless, the summation of both contemporaneous and lagged coefficients of HP in Table 7a and MM positions in Table 7b remains positive, lending support to the combined informational effects that both traders exhibit on commodity prices (see, e.g., Sockin and Xiong, 2015). Evidence shows that the lagged commodity return is negative and statistically significant across some selected commodities in both Tables 7a and 7b, reinforcing the suggestion that the corrections are not associated with the U.S. dollar, equity, or bond market nor trading activities of selected participants, but are due to a weekly time-correction relevant to commodity specifics such as grains, softs, and meats.

Evidence in Tables 7a and 7b shows that both types of traders (HP and MM) do exert a crucial role in the behavior of the commodities' prices; thus, it is important to examine the price impact while taking into account the interaction among all traders. It is beneficial to respond to the existing cross-market linkages by examining the nature of interactions among some of the most influential traders and how that interaction influences the commodity prices. Given the high correlation between HP and MM positions, we advance the empirical examination in our subsequent regressions following two steps. In the first step we take the errors from the estimation of Table 7a (hedging pressure version) as a dependent variable and run the regressions using positions of other traders including MM. The second step consists of taking the errors from the estimation of Table 7b (MM version) as a dependent variable and running the estimation process using the positions of the other traders including HP. This procedure ensures that our estimation disentangles the additional impact and contribution of the other types of traders in addition to the dominant influence of the main traders (HP or MM) as depicted in the result; the process also allows us to highlight the consistency of our results regarding these two groups of traders (HP and MM); and finally it assists us in addressing the collinearity problem.

Results in Table 8a based on Equation (9) using errors of Equation (8a), given that the main impact of the HP has shown a positive impact on price of selected commodities, show us that the MM traders' positions exert an additional positive contribution on returns of energy, metals, meats, corn, oats, and some soft commodities. Thus, Table 8a reveals that MM and NR have the ability to move the commodity prices such that higher net long positions of MM traders (and NR with few exceptions) tend to increase commodity returns. Evidence shows that SW tend to trade contrary to the MM or HP; SW net long positions have negative contributions to the commodity returns. Additionally, it is worth noting that NR positions, given the low number of traders in this category, do have an impact on the overall return but differ in sign and magnitude across selected commodities. This result pinpoints the fact that changes of positions of this group of participants are not always associated with a consistent trading strategy in commodity markets—they tend to differ, and thus those positions' influence on commodity prices differs accordingly.

Moreover, results in Table 8b based on Equation (9) using errors of Equation (8b), once the impact of MM is captured as the main influencer, show that HP contributes an additional positive effect on some of the selected commodities' returns (metals except copper, grains except oats, soft except sugar, and lean hogs), but a negative impact is seen in the case of crude oil.[6] In the case of the other types of traders (OR and NR), we notice that most of the traders' positions have positive additional impact on the futures returns, but NR positions have negative impact on crude oil returns. Under this second step of the procedure, changes of SW do not have a stable impact, as we find a negative impact on crude oil, heating oil, silver, palladium, sugar, live cattle, and lean hogs, but positive impact on cocoa and spring wheat. It is important to note that both statistical procedural steps clearly highlight the interaction property among the four types of traders and underline contemporaneous learning taking place among them, showing that each group builds trading strategies that differ across selected commodities. The significance of the interaction of hedging pressure and money managers is obvious if the coefficients of both traders from Table 7a and 7b are compared. The levels of the coefficients of both traders are quite similar, even for the lagged values. The only exception is crude oil, where HP did not play any role explaining futures returns.

In almost every market, the lagged coefficients of either hedging or speculative pressure are, if significant, negative and much lower than the contemporaneous vari-

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[6] We note that the explanatory power is very low for HP after taking into account the error term from Equation 3a "managed money" version as presented in Table 8b, since changes of MM positions show much higher explanatory power if the HP is initially taken into account as in Table 8a.

ables. So while the contemporaneous positive and significant relationship between futures returns, HP, and MM holds on a weekly basis, the lagged net position changes of hedgers and speculators are not helpful to forecast futures returns. Both trader types seem to adjust their positions in a short-term perspective to the new direction of the returns.

Overall evidence per commodity reveals that on average commodity returns are profoundly influenced by two groups of traders—hedgers and managed money funds, given their size and informational advantage—but nonetheless interactions among all participants are ubiquitous. The relative importance of hedgers and managed money funds for pricing varies for different commodities. In many commodities we find that money managers still can explain a large part of futures returns if HP with all control variables is taken into account. Especially for the crude oil market, MM can explain an additional 12 percent of the variation in the error term of Equation (8a) with HP in the regression. This confirms that hedgers' net positions or variations are less important for pricing in the crude oil commodity than for other commodities. Also on the silver, copper, oats, and feeder cattle futures markets, much explanatory power is left to money managers. Instead, the error terms of Equation (8a) with speculative pressure do not leave any explanatory power for HP. None of the adjusted R-square is above 2 percent, while some coefficients are significant. This shows that in many cases MM trading activity is more important for pricing on commodity futures markets than that of hedgers.

We anticipate that a large proportion of the net long positions and active trading strategies of managed money funds are surely behind our observations. In every commodity market, the contemporaneous net long position changes of MM are very significant and positive. In crude oil, corn, and sugar futures markets, the coefficients of managed money net long positions based on Table 7b exceed the value of one. Interestingly, the standard deviations of the net long positions (Table 1a) and the propensity to trade (Table 1b) of money managers on the crude oil, corn, and sugar markets are low. This leads to the conclusion that money managers are the most professional in these markets. They do not adjust their positions as frequently and follow the price most successfully.

Control variables:

It was not surprising that results in Tables 7a and 7b show that the U.S. dollar index movement consistently maintains a negative effect on commodity returns, which is congruent with results of some past studies (e.g., Capie et al., 2005; Joy, 2011; and many more). Even the lagged values are negatively significant for crude oil and heating oil. Only orange juice and livestock and meat futures returns are not dependent on the U.S. dollar index at all. These futures markets seem to be less influenced by global movement of relevant variables as the other futures markets, since if that were the case, traders from foreign countries surely would be affected by variations of the dollar index. However, the overall U.S. equity performance, proxied by S&P 500 index, has a concurrent positive impact on some selected commodities, notably energy, copper, palladium, and meats—that is, for example, when the U.S. equity market is doing well, the return of crude oil is gaining momentum. So increasing equity indices is seen as an indicator for increasing energy and industrial metal demand and as a driver for some soft commodities. Nevertheless, the U.S. bond market exhibits a statistically significant but negative impact on returns of some commodities (energy, some grains, and palladium) and a positive impact on gold returns. Perhaps this result grants support to the diversification argument such that when the bond market is not well performing there is an inclination on the part of investors to reverse their trading positions from the U.S. bond toward U.S. commodities to lower their overall risk. In that sense the prices of those commodities except gold reflect that additional information revealed from the U.S. bond market behavior. The implied volatility, a forward-looking volatility, measures the sentiment regarding market conditions and market uncertainty, such as a high VIX, which implies poor market conditions; our evidence in Tables 7a and 7b shows that there are a few cases when there is high uncertainty—extreme conditions—and returns of some commodities (e.g. heating oil) are higher yet return of oats is lower.

6 Conclusions

Motivated by the debate over the focus of speculators and their informational advantage over other market participants, and by some recent past studies that examined the determinants of hedging in futures markets, we were inspired to examine (1) major drivers behind the changes of the most influential traders in the commodity markets using the CFTC categorizations of the Disaggregated Commitments of Traders (DCOT), and (2) subsequently how those changes in positions—five groups of traders—affect prices of individual commodities; we simultaneously attempted to capture interactive effects among participants' positions. We show that hedgers in grains and softs except sugar, metals except gold, and meats are contrarian traders—not in all commodities, though (only 16 out of 22), which implies that hedgers reverse their positions on prior performance of the commodity in question in addition to their trading persistence in the majority of cases. In addition, speculators (specifically managed money funds, MM) who are poised for a higher propensity to trade have a short-term focus and often sell after a high performance of commodity return—they are gain seekers. Evidence illustrates that as the U.S. dollar comes under downside pressure, this type of trader's net positions improve in energy, gold, and spring wheat, but when the U.S. dollar is under upside pressure, the MM net positions increase in cocoa. Additionally, hedging pressure (hedgers' net short positions) apart from the actions of the commercial traders—actual producers or end-line users of the commodity—has a positive and statistically significant effect on MM net long positions across all selected commodities. This evidence supports the notion of contemporaneous feedback between these traders in line with some past studies that examine traders' reaction and rational investors who may prefer to ride bubbles because of predictable investor sentiment (e.g. Brunnermeier and Nagel, 2004).

The preponderance of the evidence supports the existence of important trading interactions among the most influential traders such that on average commodity returns are profoundly influenced by two groups of traders—hedgers and managed money funds, given their size and informational advantage. To learn the price impact of various participants since their interactions are relevant in price determination, we examine the relationship between trading positions and futures returns of each trader type per commodity.

Furthermore, we find that financial fundamentals proxied by equity and bond markets and the U.S. dollar account for a great deal of variability of traders' positions in some individual commodities, yet this observation is not consistent and stable across all selected commodities. Overall, the U.S. dollar movement emerges to have two effects: one is directly via its influence on commodity returns, and the other effect is indirect via its influence on the net positions of hedgers and to a lesser extent on MM net positions. In general, this observation supports our argument that behavior of commodity prices cannot be well understood without taking into account the changes of positions of influential traders, which are in turn motivated by financial fundamentals and momentum. We are *not* suggesting that selected control fundamentals are the only variables that influence market prices of individual commodities; rather we deem that we have identified another channel by which fundamentals exert lagged or contemporaneous impacts on commodity prices by triggering traders to revise their positions.

Additionally, the effect of the traders' positions on commodity prices confirms cases when hedgers' net positions (hedging pressure) and managed money funds' net positions (speculators) both play a crucial role in price determination and direction of some selected commodities. Specifically, even when controlling directly for the same financial fundamentals which initially reveal an indirectly sizeable effect on various positions, we still find that changes of positions of DCOT traders exhibit a significant effect on individual commodities, and this is more pronounced in energies, grains, and metals.

This result will prove to have some practical and policy implications. Because this study has put the spotlight on the underlying factors that influence positions of various traders including speculators, institutional investors can learn from the predictive ability of traders' positions when assessing potential performance of individual commodity futures and more importantly the relevance of some DCOT traders in the prediction of commodity returns. Hedge fund and equity-based investment strategies including rotation and tactical strategies will benefit from the main picture that emerges from this study, given its comprehensive exposure, as managers enhance their understanding regarding determinants and drivers behind the movement of some commodities in relation to some economic and financial fundamentals. Building an active, effective, equity-commodity-based strategy while taking advantage of the cyclical market conditions should only be achievable with a better understanding of the commodity futures market and its various interactive ramifications and effects of various types of traders' activities, suggesting that identification of those main trading factors offers a tremendous support to those investors who are prone to replicate trading strategies of sophisticated traders or engage in hedge fund strategies or multiple strategies including opportunistic strategies and commodity-market investing.

As all commodity futures contracts analyzed in this study are affected by position limits proposed by the CFTC, and given the important role of managed money funds and hedgers in price determination, it is of great relevance that the CFTC takes into account the role of the interaction between speculators and hedgers when determining the levels for position limits of speculators. The findings of this study might be helpful to quantify the extent to which pricing is influenced by traders' interaction. For example, in the crude oil futures market, managed money funds and small traders seem to be the main actors in pricing, while hedgers play a relatively minor role. In combination with the fact that managed money funds and small traders are driven by trend-following, position limits for managed money funds are more justified for the crude oil market than, for example, grain markets, where the impact of pricing is more evenly dispersed among all market participants. In addition to such an application, the findings of our study suggest that it is prudent to regularly observe the motivations of the market participants. As just mentioned, a commodity futures price that is driven to a large extent by traders who carry out trend-following strategies may hinder efficient pricing and may lead to bubbles or other divergence from the fundamental development of the commodity.

For future research it would be an interesting task to examine the effects of market participants' interaction on commodity pricing with the more disaggregated internal data, the Large Reporting Trading System (LTRS) of the CFTC, which were already examined in some studies (e.g. Büyüksahin and Harris, 2011). Because the LTRS consists of daily data on single large traders, an examination of their motivations and the impact of traders' interactions on higher frequencies and more disaggregated data on traders' positions could shed more light on the effect of the interaction on pricing in commodity futures markets.

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Appendix

A Tables

Table 1a: Descriptive Statistics of futures returns and position changes in percentage

	F		ΔHP		ΔMM		ΔSW		ΔOR		ΔNR	
	mean (%)	S.D. (%)	mean (%)	S.D. (%)	mean (%)	S.D. (%)	mean (%)	S.D. (%)	mean (%)	S.D. (%)	mean (%)	S.D. (%)
							Energies					
CL	-0.28	4.70	-0.01	0.78	0.02	1.18	-0.04	1.10	0.01	0. 87	<0.01	0.53
HO	-0.15	4.15	-0.04	2.52	-0.03	2.31	<-0.01	1.10	-0.01	0. 97	-0.01	1.10
RB	-0.07	4.63	-0.02	2.78	-0.01	2.49	-0.02	0.94	0.02	0. 81	<-0.01	0.87
							Metals					
GC	0.14	2.75	-0.03	2.21	<0.01	2.92	<-0.01	2.08	-0.01	1.23	-0.02	0.93
SI	0.09	4.92	<0.01	1.97	<0.01	2.82	0.02	1.80	1.80	<-0.01	-0.02	1.26
PL	-0.01	3.58	0.03	3.18	0.06	3.59	-0.03	3.15	0.02	2.07	-0.01	1.66
PA	0.20	4.66	0.01	2.96	0.07	3.49	-0.02	2.93	-0.02	1.82	-0.03	1.22
HG	-0.03	3.90	<0.01	2.47	0.06	3.62	0.06	2.03	-0.03	1.72	-0.02	1.21
							Grains					
C	0.03	4.59	<-0.01	2.13	0.02	1.99	-0.02	0.95	<-0.01	0.78	<-0.01	0.57
S	0.20	3.57	-0.02	2.77	0.03	2.37	-0.03	1.13	-0.01	1.08	-0.01	0.76
W	-0.17	4.76	<0.01	2.41	<0.01	2.43	-0.02	1.33	0.01	1.04	0.01	0.66
KW	-0.09	4.37	-0.02	2.72	<0.01	2.34	0.02	0.97	-0.04	0.97	<-0.01	0.96
MW	0.09	4.14	<-0.01	3.05	-0.02	2.11	0.02	0.65	-0.02	1.43	0.02	1.65
O	0.07	5.12	-0.06	5.05	-0.02	4.18	-0.02	1.94	-0.02	2.36	<-0.01	2.15
							Food and fiber					
CC	0.08	3.92	0.07	2.84	0.07	0.84	0.01	0.84	-0.01	0. 84	0.01	0.83
CT	-0.08	4.22	-0.05	3.83	0.03	3.01	-0.04	1.78	-0.03	1.43	-0.01	1.03
KC	-0.08	4.21	0.02	3.13	0.07	3.07	-0.03	1.25	-0.01	1.06	-0.01	0.73
JO	-0.10	4.90	-0.08	4.99	-0.12	4.76	<0.01	1.05	0.05	2.43	-0.02	1.60
SB	-0.19	4.81	-0.04	2.65	-0.04	1.98	<0.01	1.33	<0.01	1.33	-0.01	0.96
							Livestock and meats					
FC	0.02	2.04	-0.02	2.36	-0.04	3.30	-0.02	1.15	<0.01	1.93	0.03	1.90
LC	-0.03	1.88	0.05	1.89	0.04	2.01	-0.01	0.93	-0.01	1.18	0.02	0.68
LH	-0.27	3.23	0.01	2.01	0.03	2.08	-0.03	1.26	<-0.01	1.27	0.02	0.82

Note: Table 1a lists all the means and standard deviations of the futures returns (F), the position changes of hedging pressure (ΔHP), money managers' net positions changes (ΔMM), swap dealers' net position changes (ΔSW), other reportables' net position changes (ΔOR), and non reportables' net positions changes (ΔNR) on weekly data from 13 June 2006 to 31 December 2014 (447 observations). CL= WTI Crude Oil, HO=Heating Oil, RB=RBOB Gasoline, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium, HG=Copper, C=Corn, S=Soybeans, W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, O=Oats, CC=Cocoa, CT=Cotton, KC=Coffee, JO=Orange Juice, SB=Sugar, FC=Feeder Cattle, LC=Live Cattle, LH=Lean Hogs.

Table 1b: Means of net positions shares of open interest and prospensities to trade (PT) in percentage

	HP		MM		SW		OR		NR	
	mean (%)	PT (%)	mean (%)	PT (%)	mean (%)	PT (%)	mean (%)	PT (%)	mean (%)	PT (%)
					Energies					
CL	8.24	4.74	8.96	6.27	-1.66	3.47	0.46	6.09	0.48	8.40
HO	26.53	4.83	5.76	12.04	18.37	3.82	-1.14	9.30	3.54	5.69
RB	35.74	5.22	17.90	9.15	13.07	4.19	2.52	9.52	2.25	8.34
					Metals					
GC	26.73	5.34	25.88	7.57	-12.44	5.80	6.58	6.71	6.71	7.54
SI	32.37	4.66	14.94	8.78	-0.09	5.24	6.19	9.08	11.33	5.76
PL	40.07	6.40	42.74	7.13	-20.50	8.23	8.65	13.04	9.18	9.04
PA	53.95	5.31	42.23	6.32	-3.66	9.42	7.91	9.65	7.47	9.93
HG	23.68	7.13	1.12	9.14	29.79	2.73	-5.17	10.15	-2.05	7.19
					Grains					
C	30.94	3.51	11.99	6.82	23.22	2.28	3.94	5.63	-8.21	2.95
S	33.13	4.82	15.88	8.34	21.14	2.95	2.20	7.79	-6.09	4.29
W	26.83	5.27	0.40	6.21	34.09	2.33	-2.73	7.52	-4.94	4.46
KW	32.46	4.39	14.64	6.90	19.56	3.62	3.59	8.23	-5.32	5.89
MW	20.17	4.73	14.15	9.91	3.51	19.52	4.26	17.45	-1.76	6.14
O	40.51	6.00	11.30	15.66	14.64	3.60	6.78	16.04	7.68	9.82
					Food and fiber					
CC	26.98	3.60	16.82	7.21	5.99	4.64	1.55	12.11	2.62	11.08
CT	44.23	6.40	11.08	8.23	30.00	3.00	0.18	8.97	2.97	8.22
KC	35.37	4.66	6.45	8.38	23.86	2.45	3.71	9.23	1.36	12.56
JO	46.20	6.13	20.04	11.91	12.10	3.78	7.85	11.72	6.20	10.75
SB	29.90	4.23	9.38	6.62	15.25	2.87	3.64	7.95	1.64	7.03
					Livestock and meats					
FC	3.32	8.29	18.79	8.68	12.41	6.11	-4.59	12.59	-23.29	4.86
LC	35.07	3.75	17.35	5.56	30.59	1.54	-3.84	8.42	-9.03	4.29
LH	36.62	4.73	10.09	7.18	32.17	2.06	-1.40	9.66	-4.23	4.87

Note: Table 1b lists all the means (for HP: $\frac{short\ positions_t - long\ positions_t}{open\ interest_t}$; for all other categories: $\frac{long\ positions_t - short\ positions_t}{open\ interest_t}$) and the prospensities to trade ($PT_t = \frac{abs(long\ positions_t - long\ positions_{t-1}) + abs(short\ positions_t - short\ positions_{t-1})}{long\ positions_{t-1} + short\ positions_{t-1}}$) of hedging pressure (HP), money managers (MM), swap dealers (SW), other reportables (OR), and non reportables (NR) on weekly data from 13 June 2006 to 31 December 2014 (447 observations). CL= WTI Crude Oil, HO=Heating Oil, RB=RBOB Gasoline, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium, HG=Copper, C=Corn, S=Soybeans, W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, O=Oats, CC=Cocoa, CT=Cotton, KC=Coffee, JO=Orange Juice, SB=Sugar, FC=Feeder Cattle, LC=Live Cattle, LH=Lean Hogs.

Table 2: Hedging pressure as the dependent variable, the "US approach"

	HP(-1)	F(-1)	DI	DI(-1)	SP	SP(-1)	BIUS	BIUS (-1)	VIX	VIX(-1)	R² adj.
Energies											
CL	-0.00	-0.01	-0.03	-0.01	-0.03	-0.01	0.00	-0.00	-0.01**	-0.01	0.00
	(-0.03)	(-0.79)	(-0.93)	(-0.20)	(-1.11)	(-0.30)	(0.03)	(-0.05)	(-2.08)	(-1.04)	
HO	0.01	0.07*	-0.19*	-0.22**	0.23***	-0.00	0.00	-0.43**	0.03*	-0.02	0.09
	(0.27)	(1.95)	(-1.80)	(-2.38)	(3.19)	(-0.07)	(0.01)	(-2.00)	(1.74)	(-1.17)	
RB	0.12***	0.02	-0.06	-0.23*	0.25**	-0.13	-0.09	-0.33	0.03	-0.05**	0.07
	(2.62)	(0.51)	(-0.40)	(-1.94)	(2.28)	(-1.60)	(-0.26)	(-1.37)	(1.34)	(-2.33)	
Metals											
GC	0.05	0.07	-0.55***	-0.20*	-0.07	-0.12*	-0.06	-0.11	-0.01	-0.00	0.09
	(0.88)	(1.46)	(-5.72)	(-1.86)	(-1.12)	(-1.89)	(-0.28)	(-0.57)	(-0.63)	(-0.26)	
SI	0.04	0.04*	-0.21**	0.00	-0.02	0.01	0.18	0.09	-0.00	0.00	0.01
	(0.82)	(1.68)	(-2.07)	(0.03)	(-0.22)	(0.11)	(0.92)	(0.48)	(-0.12)	(0.07)	
PL	0.01	0.20***	-0.31**	-0.02	0.14	0.01	-0.19	-0.50*	0.02	-0.01	0.08
	(0.31)	(4.15)	(-2.26)	(-0.11)	(1.54)	(0.16)	(-0.70)	(-1.79)	(0.75)	(-0.44)	
PA	0.13***	0.07**	-0.32**	-0.16	0.10	-0.10	-0.20	0.37	0.01	-0.04*	0.07
	(2.72)	(2.08)	(-2.49)	(-1.18)	(1.10)	(-1.18)	(-0.76)	(1.39)	(0.24)	(-1.80)	
HG	0.11**	0.11***	-0.32***	-0.01	0.04	-0.04	-0.38*	0.07	-0.00	-0.02	0.08
	(2.26)	(2.98)	(-2.83)	(-0.11)	(0.76)	(-0.59)	(-1.82)	(0.34)	(-0.28)	(-1.21)	
Grains											
C	0.25***	0.03	-0.26***	0.02	0.12	-0.05	-0.22	0.26	0.03**	-0.03	0.12
	(4.71)	(1.37)	(-3.00)	(0.33)	(2.68)	(-0.76)	(-1.26)	(1.19)	(2.13)	(-1.50)	
S	0.17***	0.08*	-0.21**	0.05	0.22***	0.02	-0.31	0.11	0.03	-0.01	0.10
	(2.92)	(1.94)	(-2.22)	(0.35)	(2.64)	(0.25)	(-1.20)	(0.51)	(1.18)	(-0.46)	
W	0.16***	0.06**	-0.48***	-0.05	0.06	-0.08	-0.25	0.34	0.03	-0.02	0.12
	(2.93)	(2.27)	(-4.72)	(-0.47)	(0.92)	(-1.26)	(-1.18)	(1.61)	(1.43)	(-1.10)	
KW	0.30***	0.11***	-0.28**	0.03	0.14**	-0.15**	0.03	0.27	0.00	-0.04	0.20
	(5.95)	(3.53)	(-2.54)	(0.24)	(1.97)	(-2.14)	(0.15)	(1.21)	(0.15)	(-2.09)	
MW	0.14***	0.16***	-0.28**	-0.08	0.07	0.04	-0.02	0.13	-0.01	0.00	0.10
	(2.97)	(3.86)	(-2.57)	(-0.66)	(0.76)	(0.44)	(-0.09)	(0.43)	(-0.24)	(0.02)	
O	0.18***	0.20***	-0.79***	0.15	0.02	0.08	-0.90	-0.68	0.03	-0.00	0.14
	(2.82)	(3.33)	(-3.45)	(0.66)	(0.13)	(0.73)	(-1.89)	(-1.69)	(0.66)	(-0.10)	
Food and fiber											
CC	0.24***	0.12***	-0.40***	-0.13	0.14*	0.06	-0.21	-0.32	0.03	0.06***	0.19
	(4.89)	(3.22)	(-3.42)	(-1.06)	(1.86)	(0.74)	(-0.87)	(-1.36)	(1.34)	(2.83)	
CT	0.29***	0.02	-0.10	-0.17	0.13	-0.04	-0.20	-0.36	-0.02	0.04	0.10
	(5.91)	(0.41)	(-0.63)	(-1.04)	(1.27)	(-0.42)	(-0.59)	(-1.06)	(-0.70)	(0.16)	
KC	0.16***	0.15***	-0.29**	-0.09	0.14	-0.04	-0.27	-0.35	0.02	0.00	0.12
	(2.85)	(3.42)	(-2.13)	(-0.61)	(1.61)	(-0.43)	(-0.99)	(-1.26)	(0.71)	(0.15)	
JO	0.13**	0.26***	-0.62***	0.06	0.02	0.01	-0.55	0.17	-0.00	-0.04	0.14
	(2.37)	(4.58)	(-2.89)	(0.26)	(0.17)	(0.10)	(-1.27)	(0.40)	(-0.01)	(-1.05)	
SB	0.32***	-0.01	-0.20*	-0.08	0.08	-0.09	-0.06	-0.21	-0.00	-0.04**	0.14
	(6.48)	(-0.20)	(-1.77)	(-0.72)	(1.14)	(-1.26)	(-0.25)	(-0.93)	(-0.06)	(-2.34)	
Livestock and meats											
FC	0.22***	0.42***	0.08	-0.18*	0.07	-0.10	0.41**	-0.23	-0.03	0.00	0.21
	(4.82)	(8.07)	(0.80)	(-1.85)	(1.10)	(-1.57)	(2.11)	(-1.20)	(-1.39)	(0.06)	
LC	0.11**	0.26***	-0.09	-0.08	0.02	-0.02	-0.38	-0.20	0.02	0.02	0.08
	(2.31)	(5.44)	(-1.08)	(-1.00)	(0.36)	(-0.35)	(-2.29)	(-1.22)	(1.29)	(1.15)	
LH	0.29***	0.09***	-0.11	0.00	0.01	-0.04	-0.22*	-0.10	0.01	-0.00	0.13
	(5.97)	(3.37)	(-1.27)	(0.01)	(0.19)	(-0.67)	(-1.65)	(-0.55)	(0.59)	(-0.21)	

Note: Table 2 lists all the coefficients and t-statistics in parentheses of equation (6): $\Delta HP_{t,i} = \alpha_i + \delta \Delta HP_{t-1,i} + \gamma_i r_{t-1,i} + \beta' X + \omega_i D_{FebBreak} + \varepsilon_t$. Regressions were calculated by OLS, and Newey-West standard errors are calculated for regressions with serial correlated and/or heteroskedastic error terms. CL= WTI Crude Oil, HO=Heating Oil, RB=RBOB Gasoline, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium, HG=Copper, C=Corn, S=Soybeans, W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, O=Oats, CC=Cocoa, CT=Cotton, KC=Coffee, JO=Orange Juice, SB=Sugar, FC=Feeder Cattle, LC=Live Cattle, LH=Lean Hogs; HP(-1)=one lagged hedging pressure, F(-1)=one lagged futures return, DI=Dollar Index, DI(-1) one lagged Dollar Index, SP=S&P 500, SP(-1)=one lagged S&P 500, BIUS=Citigroup WGBI US all maturities, BIUS(-1)=one lagged Citigroup WGBI US all maturities, VIX=S&P 500 Volatility Index, VIX(-1)= one lagged S&P 500 Volatility Index, FEB= dummy for February effect. ***, ***, * denote significance at 1, 5 and 10 percent level, respectively.

Table 3: Money managers' net long position changes as the dependent variable, the "US approach"

	MM(-1)	F(-1)	HP	DI	DI(-1)	SP	SP(-1)	BIUS	BIUS (-1)	VIX	VIX(-1)	R^2 adj.
						Energies						
CL	-0.03	0.03*	0.49***	-0.19***	-0.07	0.11***	-0.04	-0.19**	-0.02	0.01	-0.01	0.23
	(-0.57)	(1.90)	(7.57)	(-4.12)	(-1.48)	(3.61)	(-1.39)	(-2.01)	(-0.23)	(1.08)	(-0.76)	
HO	0.04	0.02	0.73***	-0.13**	0.01	-0.01	0.00	-0.15	-0.00	-0.01	0.00	0.68
	(0.99)	(1.43)	(20.48)	(-2.33)	(0.13)	(-0.19)	(0.03)	(-1.27)	(-0.02)	(-0.72)	(0.03)	
RB	0.04	0.01	0.76***	-0.10**	-0.02	0.02	-0.03	-0.16*	-0.25**	0.01	-0.01	0.76
	(1.17)	(0.74)	(27.22)	(-2.15)	(-0.26)	(0.58)	(-0.72)	(-1.82)	(-2.31)	(0.73)	(-1.16)	
						Metals						
GC	0.01	0.01	0.94***	-0.16*	-0.15	0.02	-0.05	0.28*	-0.02	-0.01	-0.03	0.57
	(0.16)	(0.38)	(13.81)	(-1.94)	(-1.46)	(0.27)	(-1.02)	(1.72)	(-0.10)	(-0.84)	(-1.57)	
SI	0.14***	0.03	0.82***	-0.09	-0.08	0.13**	-0.06	0.16	-0.20	-0.01	-0.04**	0.45
	(3.30)	(1.02)	(15.61)	(-0.94)	(-0.72)	(2.17)	(-0.96)	(0.81)	(-1.04)	(-0.63)	(-2.56)	
PL	0.11**	0.00	0.61***	-0.19	0.00	-0.08	0.01	-0.46*	0.41	-0.03	-0.06***	0.36
	(2.36)	(0.08)	(9.27)	(-1.39)	(0.03)	(-0.87)	(0.08)	(-1.94)	(1.45)	(-1.42)	(-2.99)	
PA	0.10**	-0.03	0.69***	-0.08	0.03	0.10	-0.10	-0.12	-0.07	0.00	-0.04*	0.39
	(2.47)	(-1.02)	(14.67)	(-0.61)	(0.23)	(1.31)	(-1.19)	(-0.49)	(-0.27)	(0.01)	(-1.78)	
HG	0.06	-0.03	1.05***	-0.05	-0.10	-0.02	-0.01	-0.32	-0.04	-0.05***	-0.03*	0.57
	(1.26)	(-0.70)	(15.45)	(-0.51)	(-1.15)	(-0.29)	(-0.20)	(-1.51)	(-0.17)	(-2.64)	(-1.67)	
						Grains						
C	0.06**	0.04***	0.77***	-0.03	-0.02	-0.01	0.00	0.11	-0.21**	0.00	0.01	0.73
	(2.17)	(2.83)	(30.86)	(-0.65)	(-0.43)	(-0.23)	(0.00)	(1.11)	(-2.14)	(0.31)	(1.63)	
S	0.03	0.02	0.72***	-0.05	-0.02	-0.00	0.06	-0.06	-0.02	0.00	0.01	0.75
	(1.20)	(1.06)	(33.20)	(-0.85)	(-0.33)	(-0.04)	(1.64)	(-0.56)	(-0.19)	(0.35)	(0.99)	
W	0.06**	0.03**	0.83***	0.04	0.02	-0.02	-0.02	-0.10	-0.11	-0.00	-0.00	0.70
	(2.09)	(2.06)	(29.50)	(0.64)	(0.30)	(-0.44)	(-0.53)	(-0.78)	(-0.89)	(-0.10)	(-0.31)	
KW	0.05	0.05***	0.70***	-0.06	0.01	-0.04	0.03	-0.12	-0.00	0.01	0.01	0.72
	(1.60)	(2.77)	(28.45)	(-1.05)	(0.24)	(-1.18)	(0.75)	(-1.06)	(-0.03)	(0.69)	(1.23)	
MW	0.03	0.00	0.48***	-0.15**	-0.09	0.05	-0.02	0.00	0.11	0.01	-0.01	0.52
	(0.73)	(0.15)	(19.40)	(-2.30)	(-1.29)	(1.23)	(-0.45)	(0.02)	(0.93)	(1.20)	(-0.82)	
O	0.01	0.09***	0.57***	0.06	0.00	-0.11	0.05	-0.11	0.36	-0.03	-0.01	0.52
	(0.26)	(2.71)	(19.28)	(0.46)	(0.00)	(-1.28)	(0.63)	(-0.42)	(1.34)	(-1.35)	(-0.30)	
						Food and fiber						
CC	0.04	0.07***	0.79***	0.11*	-0.03	-0.05	-0.06**	-0.11	-0.12	-0.01	-0.01	0.77
	(1.33)	(3.77)	(15.48)	(1.94)	(-0.47)	(-1.19)	(-2.12)	(-0.91)	(-0.95)	(-1.12)	(-1.41)	
CT	0.10***	0.05**	0.60***	-0.07	-0.04	0.03	-0.02	-0.00	0.14	0.01	-0.01	0.65
	(3.19)	(2.07)	(25.63)	(-0.91)	(-0.51)	(0.56)	(-0.40)	(-0.01)	(0.82)	(0.91)	(-0.76)	
KC	0.04	0.10***	0.79***	0.08	-0.05	0.09**	0.05	0.01	0.09	0.03**	0.01	0.78
	(1.38)	(4.65)	(33.36)	(1.24)	(-0.68)	(2.00)	(1.21)	(0.07)	(0.64)	(2.45)	(0.86)	
JO	0.09***	0.15***	0.72***	-0.17	0.21*	-0.02	0.07	-0.11	0.35	0.00	0.02	0.74
	(2.97)	(5.01)	(28.21)	(-1.46)	(1.84)	(-0.30)	(1.02)	(-0.47)	(1.54)	(0.11)	(1.22)	
SB	0.09***	0.05***	0.58***	0.03	0.07	-0.01	0.06*	-0.08	-0.02	0.00	0.02**	0.66
	(2.73)	(3.91)	(25.87)	(0.49)	(1.43)	(-0.31)	(1.73)	(-0.73)	(-0.20)	(0.35)	(2.13)	
						Livestock and meats						
FC	0.10**	0.19***	0.83***	0.02	0.04	0.01	-0.09	0.22	-0.12	0.00	-0.01	0.47
	(2.31)	(2.66)	(11.00)	(0.24)	(0.36)	(0.17)	(-1.11)	(0.87)	(-0.47)	(0.12)	(-0.45)	
LC	0.06*	0.17***	0.76***	-0.02	0.11	-0.05	-0.08**	-0.11	0.04	-0.01	-0.01	0.60
	(1.93)	(4.76)	(22.09)	(-0.33)	(1.95)	(-1.38)	(-2.04)	(-0.93)	(0.37)	(-1.44)	(-1.29)	
LH	0.04	0.12***	0.67***	0.02	0.01	0.03	-0.01	-0.01	0.02	-0.00	0.00	0.52
	(0.88)	(4.82)	(17.22)	(0.36)	(0.09)	(0.68)	(-0.37)	(-0.10)	(0.19)	(-0.04)	(0.02)	

Note: Table 3 lists all the coefficients and t-statistics in parentheses of equation (7): $\Delta pos_{t,i}^{j} = \alpha_i + \delta_i \Delta pos_{t-1,i}^{j} + \gamma_i r_{t-1,i} + \theta_i \Delta HP_{t,i} + \beta' X + \omega_i D_{FebBreak} + \varepsilon_{t,i}$. Regressions were calculated by OLS, and Newey-West standard errors are calculated for regressions with serial correlated and/or heteroskedastic error terms. CL= WTI Crude Oil, HO=Heating Oil, RB=RBOB Gasoline, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium, HG=Copper, C=Corn, S=Soybeans, W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, O=Oats, CC=Cocoa, CT=Cotton, KC=Coffee, JO=Orange Juice, SB=Sugar, FC=Feeder Cattle, LC=Live Cattle, LH=Lean Hogs; MM(-1)=one lagged money managers' net long position changes, F(-1)=one lagged futures return, HP=hedging pressure, DI=Dollar Index, DI(-1) one lagged Dollar Index, SP=S&P 500, SP(-1)=one lagged S&P 500, BIUS=Citigroup WGBI US all maturities, BIUS(-1)=one lagged Citigroup WGBI US all maturities, VIX=S&P 500 Volatility Index, VIX(-1)= one lagged S&P 500 Volatility Index, FEB= dummy for February effect. ***, ***, * denote significance at 1, 5 and 10 percent level, respectively.

Table 4: Swap dealers' net long position changes as the dependent variable, the "US approach"

	SW(-1)	F(-1)	HP	DI	DI(-1)	SP	SP(-1)	BIUS	BIUS (-1)	VIX	VIX(-1)	R^2 adj.
						Energies						
CL	0.18***	-0.04**	0.28***	0.16***	-0.01	-0.08***	0.01	0.06	-0.01	-0.01	0.00	0.17
	(3.92)	(-2.28)	(3.57)	(3.07)	(-0.15)	(-2.81)	(0.19)	(0.75)	(-0.08)	(-0.76)	(0.04)	
HO	-0.01	-0.05***	-0.00	0.14***	-0.08	0.02	-0.03	0.12	0.01	0.01*	-0.01	0.05
	(-0.18)	(-3.18)	(-0.01)	(3.14)	(-1.55)	(0.81)	(-0.73)	(1.27)	(0.05)	(1.82)	(-1.59)	
RB	0.15***	-0.03**	0.09***	0.04	0.01	-0.04	0.00	0.04	0.12	-0.00	-0.00	0.10
	(3.37)	(-2.02)	(3.93)	(1.20)	(0.14)	(-1.10)	(0.07)	(0.50)	(1.31)	(-0.05)	(-0.55)	
						Metals						
GC	0.05	-0.01	-0.20***	0.21**	0.10	-0.08	0.01	-0.37**	0.09	0.00	0.03*	0.11
	(1.09)	(-0.13)	(-4.53)	(2.31)	(1.05)	(-1.37)	(0.30)	(-2.01)	(0.48)	(0.30)	(1.74)	
SI	0.11	-0.03	-0.16**	0.15*	0.01	-0.05	0.02	0.13	0.18	0.02	0.02	0.11
	(1.59)	(-1.42)	(-2.17)	(1.87)	(0.07)	(-0.95)	(0.52)	(0.72)	(1.32)	(1.61)	(1.63)	
PL	0.04	-0.05	0.04	0.51***	-0.03	0.11	-0.06	0.30	-0.18	0.00	0.03	0.02
	(0.78)	(-1.04)	(0.84)	(3.59)	(-0.26)	(1.19)	(-0.66)	(1.03)	(-0.61)	(0.19)	(1.30)	
PA	0.06	0.01	-0.03	0.29**	-0.05	-0.12	-0.01	0.25	0.27	0.01	0.01	0.03
	(1.27)	(0.17)	(-0.55)	(2.20)	(-0.40)	(-1.46)	(-0.16)	(0.94)	(0.99)	(0.27)	(0.62)	
HG	0.14***	-0.05**	0.06	0.29***	-0.04	0.04	0.01	0.40**	0.36**	0.04**	0.01	0.09
	(2.84)	(-1.79)	(1.51)	(3.25)	(-0.46)	(0.77)	(0.24)	(2.23)	(1.97)	(2.27)	(0.68)	
						Grains						
C	0.25***	-0.03**	0.14***	0.01	-0.06*	-0.02	-0.02	0.04	0.15**	-0.00	-0.01	0.17
	(6.24)	(-2.44)	(4.89)	(0.22)	(-1.78)	(-0.62)	(-0.73)	(0.62)	(2.13)	(-0.22)	(-1.11)	
S	0.23***	0.01	0.09***	0.06	0.00	0.01	-0.05	0.02	0.07	-0.00	-0.03***	0.10
	(4.86)	(0.38)	(4.57)	(1.18)	(0.07)	(0.29)	(-1.53)	(0.16)	(0.66)	(-0.48)	(-3.19)	
W	0.20***	-0.03*	0.19***	0.04	-0.08	-0.01	0.00	0.16	0.23**	0.00	-0.01	0.17
	(4.52)	(-1.87)	(7.61)	(0.77)	(-1.51)	(-0.33)	(0.09)	(1.40)	(2.01)	(0.10)	(-1.17)	
KW	0.12***	-0.02	0.13***	0.08*	-0.02	0.04	-0.03	0.21**	0.07	-0.01	-0.01	0.13
	(2.60)	(-1.60)	(6.78)	(1.80)	(-0.37)	(1.22)	(-1.06)	(2.27)	(0.72)	(-1.40)	(-1.11)	
MW	0.12***	-0.01	0.05***	0.01	0.01	0.02	0.01	-0.00	0.01	0.00	-0.00	0.04
	(2.64)	(-1.51)	(4.42)	(0.21)	(0.22)	(0.92)	(0.53)	(-0.08)	(0.11)	(0.53)	(-0.70)	
O	-0.03	-0.05***	0.15***	0.02	0.08	0.02	-0.01	-0.13	-0.38	0.01	0.00	0.15
	(-0.25)	(-3.16)	(3.04)	(0.16)	(0.70)	(0.38)	(-0.14)	(-0.40)	(-1.53)	(0.50)	(0.01)	
						Food and fiber						
CC	0.09*	-0.02	0.06	-0.00	0.06	0.06**	0.02	0.12	0.09	0.01	0.01	0.06
	(1.94)	(-1.45)	(4.09)	(-0.04)	(1.53)	(2.38)	(0.65)	(1.57)	(1.25)	(1.42)	(1.31)	
CT	0.26***	-0.04**	0.18***	0.11*	0.00	-0.08	0.06	-0.07	-0.04	-0.01	0.02	0.24
	(5.41)	(-2.20)	(6.35)	(1.79)	(0.04)	(-1.50)	(1.18)	(-0.47)	(-0.32)	(-0.81)	(1.45)	
KC	0.20***	-0.06***	0.13***	-0.00	0.03	-0.04	-0.02	0.03	-0.09	-0.01	-0.00	0.15
	(4.62)	(-4.38)	(6.93)	(-0.03)	(0.58)	(-1.11)	(-0.46)	(0.27)	(-0.91)	(-1.43)	(-0.21)	
JO	0.15***	-0.02*	0.04***	0.12**	-0.05	0.03	-0.06**	0.21**	-0.12	0.00	-0.01	0.06
	(3.19)	(-1.74)	(3.99)	(2.52)	(-1.06)	(1.04)	(-2.04)	(2.22)	(-1.27)	(0.05)	(-0.87)	
SB	0.14***	-0.04***	0.19***	0.06	-0.09	-0.02	-0.07**	0.10	0.14	-0.02**	-0.02**	0.21
	(3.14)	(-3.67)	(8.17)	(1.10)	(-1.63)	(-0.61)	(-2.05)	(0.96)	(1.24)	(-2.45)	(-2.04)	
						Livestock and meats						
FC	0.24***	-0.07**	0.11***	0.04	0.01	-0.00	0.07**	0.07	0.07	-0.00	0.02*	0.09
	(3.94)	(-2.26)	(5.28)	(0.60)	(0.28)	(-0.01)	(2.00)	(0.56)	(0.51)	(-0.08)	(1.90)	
LC	0.10**	-0.06**	0.16***	0.02	-0.05	-0.00	0.03	-0.06	0.02	0.00	0.01**	0.11
	(2.21)	(-2.32)	(6.74)	(0.48)	(-1.30)	(-0.15)	(1.25)	(-0.76)	(0.22)	(0.59)	(2.03)	
LH	0.06	-0.03*	0.11***	0.08	-0.01	0.05	-0.02	0.10	-0.07	-0.00	0.01	0.02
	(1.25)	(-1.71)	(3.64)	(1.39)	(-0.13)	(1.42)	(-0.50)	(0.90)	(-0.57)	(-0.24)	(0.50)	

Note: Table 4 lists all the coefficients and t-statistics in parentheses of equation (7): $\Delta pos_{t,i}^{j} = \alpha_i + \delta_i \Delta pos_{t-1,i}^{j} + \gamma_i r_{t-1,i} + \theta_i \Delta HP_{t,i} + \beta' X + \omega_i D_{FebBreak} + \varepsilon_{t,i}$. Regressions were calculated by OLS, and Newey-West standard errors are calculated for regressions with serial correlated and/or heteroskedastic error terms. CL= WTI Crude Oil, HO=Heating Oil, RB=RBOB Gasoline, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium, HG=Copper, C=Corn, S=Soybeans, W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, O=Oats, CC=Cocoa, CT=Cotton, KC=Coffee, JO=Orange Juice, SB=Sugar, FC=Feeder Cattle, LC=Live Cattle, LH=Lean Hogs; SW(-1)=one lagged swap dealers' net long position changes, F(-1)=one lagged futures return, HP= hedging pressure, DI=Dollar Index, DI(-1) one lagged Dollar Index, SP=S&P 500, SP(-1)=one lagged S&P 500, BIUS=Citigroup WGBI US all maturities, BIUS(-1)=one lagged Citigroup WGBI US all maturities, VIX=S&P 500 Volatility Index, VIX(-1)= one lagged S&P 500 Volatility Index, FEB= dummy for February effect. ***, ***, * denote significance at 1, 5 and 10 percent level, respectively.

Table 5: Other reportables' net long position changes as the dependent variable, the "US approach"

	OR(-1)	F(-1)	HP	DI	DI(-1)	SP	SP(-1)	BIUS	BIUS (-1)	VIX	VIX(-1)	R^2 adj.
Energies												
CL	-0.10*	-0.01	0.17**	0.01	0.04	-0.01	0.05*	0.11	0.02	-0.00	0.01	0.03
	(-1.73)	(-1.10)	(2.54)	(0.26)	(1.06)	(-0.38)	(1.84)	(1.33)	(0.23)	(-0.25)	(1.56)	
HO	0.04	-0.02	-0.01	0.01	0.06*	-0.02	0.01	0.06	-0.02	-0.01	0.01	0.01
	(0.54)	(-1.44)	(-0.69)	(0.12)	(1.73)	(-0.76)	(0.33)	(0.82)	(-0.26)	(-0.83)	(0.99)	
RB	0.13*	-0.02**	-0.01	0.04	-0.03	-0.03*	0.01	0.13**	-0.02	-0.01	0.01	0.03
	(1.87)	(-2.19)	(-0.55)	(1.09)	(-0.72)	(-1.71)	(0.59)	(2.36)	(-0.42)	(-1.40)	(1.26)	
Metals												
GC	-0.02	-0.01	0.04	0.00	0.02	-0.01	0.07*	0.02	0.10	0.01	-0.00	0.00
	(-0.47)	(-0.37)	(1.37)	(0.06)	(0.26)	(-0.40)	(1.90)	(0.20)	(0.86)	(0.61)	(-0.11)	
SI	-0.14***	-0.03**	0.05	0.09*	-0.05	-0.06*	-0.02	-0.18*	-0.08	-0.01	0.00	0.03
	(-2.79)	(-2.46)	(1.60)	(1.69)	(-0.87)	(-1.89)	(-0.52)	(-1.71)	(-0.73)	(-0.80)	(0.20)	
PL	0.05	-0.02	0.19***	-0.04	0.07	-0.06	0.11*	-0.16	-0.14	0.02	0.04**	0.08
	(0.80)	(-0.76)	(4.02)	(-0.34)	(0.69)	(-0.65)	(1.66)	(-0.89)	(-0.69)	(1.19)	(2.39)	
PA	-0.18**	0.00	0.16***	-0.04	-0.03	0.02	0.03	-0.10	-0.09	0.01	0.01	0.10
	(-2.11)	(0.04)	(4.25)	(-0.48)	(-0.45)	(0.31)	(0.88)	(-0.66)	(-0.48)	(0.97)	(0.86)	
HG	-0.03	0.03	-0.26***	-0.19***	0.08	-0.05	0.02	-0.05	-0.09	0.02	0.02	0.15
	(-0.68)	(1.12)	(-8.13)	(-2.61)	(1.13)	(-1.01)	(0.32)	(-0.31)	(-0.61)	(1.63)	(1.28)	
Grains												
C	0.01	-0.01	0.06**	-0.01	0.06*	0.00	0.03	-0.11	0.06	-0.00	-0.00	0.03
	(0.21)	(-1.42)	(3.22)	(-0.18)	(1.80)	(0.21)	(1.29)	(-1.53)	(0.89)	(-0.28)	(-0.49)	
S	0.03	-0.02	0.05***	0.05	0.03	-0.00	-0.03	0.08	-0.03	-0.00	0.00	0.01
	(0.70)	(-1.10)	(2.67)	(1.00)	(0.69)	(-0.05)	(-0.92)	(0.83)	(-0.32)	(-0.13)	(0.29)	
W	-0.04	-0.02**	-0.11***	-0.05	0.02	0.01	0.00	0.05	-0.17*	-0.00	0.01	0.08
	(-0.78)	(-2.19)	(-5.22)	(-1.04)	(0.41)	(0.37)	(0.05)	(0.51)	(-1.89)	(-0.34)	(1.00)	
KW	-0.05	-0.03**	0.06***	0.04	0.04	0.00	-0.02	0.08	0.03	-0.00	-0.01*	0.02
	(-0.95)	(-2.37)	(3.28)	(0.86)	(0.99)	(0.16)	(-1.03)	(0.92)	(0.32)	(-0.23)	(-1.76)	
MW	-0.05	-0.01	0.17***	0.17***	0.03	-0.02	-0.04	-0.01	-0.27**	-0.01	-0.00	0.13
	(-1.03)	(-0.58)	(7.78)	(2.87)	(0.44)	(-0.42)	(-1.15)	(-0.07)	(-2.22)	(-1.10)	(-0.22)	
O	0.16	-0.04	0.07*	-0.10	-0.00	0.04	-0.05	0.16	-0.23	0.03*	-0.00	0.05
	(1.53)	(-1.53)	(1.79)	(-1.06)	(-0.02)	(0.80)	(-0.68)	(1.02)	(-0.98)	(1.91)	(-0.20)	
Food and fiber												
CC	-0.07	-0.03***	-0.01	-0.02	-0.02	-0.04	-0.01	0.11	-0.09	-0.01	0.00	0.02
	(-0.78)	(-2.76)	(-0.25)	(-0.49)	(-0.39)	(-1.31)	(-0.38)	(1.63)	(-1.19)	(-1.17)	(0.58)	
CT	0.13***	-0.03	0.04**	0.03	0.04	0.05	-0.03	0.01	-0.21	0.01	0.00	0.02
	(2.80)	(-1.56)	(2.26)	(0.43)	(0.58)	(1.10)	(-0.83)	(0.09)	(-1.59)	(0.56)	(0.00)	
KC	-0.00	-0.04***	-0.03*	-0.04	0.05	-0.03	-0.03	-0.06	0.05	-0.01	-0.01	0.05
	(-0.01)	(-3.10)	(-1.89)	(-0.84)	(1.11)	(-1.09)	(-1.01)	(-0.60)	(0.51)	(-1.13)	(-0.76)	
JO	0.16***	-0.12***	0.06**	0.17	-0.11	-0.00	-0.07	-0.14	-0.18	0.00	-0.02	0.08
	(3.43)	(-4.79)	(2.50)	(1.58)	(-1.06)	(-0.04)	(-0.95)	(-0.66)	(-0.83)	(0.11)	(-1.11)	
SB	0.14**	-0.02**	0.02	-0.01	-0.03	-0.00	-0.00	-0.00	-0.19**	0.01**	0.00	0.04
	(2.54)	(-2.30)	(0.95)	(-0.34)	(-0.97)	(-0.16)	(-0.11)	(-0.03)	(-2.49)	(2.52)	(0.46)	
Livestock and meats												
FC	0.01	-0.07	0.15***	-0.01	0.04	0.04	-0.05	-0.17	-0.21	0.01	-0.01	0.01
	(0.23)	(-1.28)	(2.72)	(-0.13)	(0.39)	(0.72)	(-0.85)	(-0.80)	(-1.08)	(0.99)	(-0.50)	
LC	0.07	-0.11***	0.17***	-0.05	-0.00	0.02	0.06*	0.03	-0.00	0.01	0.01	0.06
	(1.41)	(-3.38)	(5.41)	(-0.89)	(-0.09)	(0.52)	(1.89)	(0.28)	(-0.00)	(1.03)	(0.62)	
LH	0.05	-0.03	0.12***	-0.04	0.01	-0.07	0.01	0.05	0.01	0.01	-0.00	0.05
	(0.74)	(-1.64)	(3.93)	(-0.85)	(0.17)	(-2.04)	(0.29)	(0.48)	(0.11)	(1.06)	(-0.24)	

Note: Table 5 lists all the coefficients and t-statistics in parentheses of equation (7):
$\Delta pos_{t,i}^{j} = \alpha_i + \delta_i \Delta pos_{t-1,i}^{j} + \gamma_i r_{t-1,i} + \theta_i \Delta HP_{t,i} + \beta' X + \omega_i D_{FebBreak} + \varepsilon_{t,i}$. Regressions were calculated by OLS, and Newey-West standard errors are calculated for regressions with serial correlated and/or heteroskedastic error terms. CL= WTI Crude Oil, HO=Heating Oil, RB=RBOB Gasoline, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium, HG=Copper, C=Corn, S=Soybeans, W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, O=Oats, CC=Cocoa, CT=Cotton, KC=Coffee, JO=Orange Juice, SB=Sugar, FC=Feeder Cattle, LC=Live Cattle, LH=Lean Hogs; OR(-1)=one lagged other reportables' net long position changes, F(-1)=one lagged futures return, HP=hedging pressure, DI=Dollar Index, DI(-1) one lagged Dollar Index, SP=S&P 500, SP(-1)=one lagged S&P 500, BIUS=Citigroup WGBI US all maturities, BIUS(-1)=one lagged Citigroup WGBI US all maturities, VIX=S&P 500 Volatility Index, VIX(-1)= one lagged S&P 500 Volatility Index, FEB= dummy for February effect. ***, ***, * denote significance at 1, 5 and 10 percent level, respectively.

Table 6: Non reportables' net long position changes as the dependent variable, the "US approach"

	NR(-1)	F(-1)	HP	DI	DI(-1)	SP	SP(-1)	BIUS	BIUS (-1)	VIX	VIX(-1)	R^2 adj.
						Energies						
CL	-0.25***	0.03***	0.06*	0.01	0.01	-0.02	-0.01	0.05	0.03	-0.00	-0.00	0.18
	(-4.83)	(5.61)	(1.85)	(0.43)	(0.49)	(-1.51)	(-0.83)	(1.22)	(0.71)	(-0.88)	(-1.22)	
HO	-0.04	0.03***	0.28***	-0.02	0.02	0.00	0.02	-0.02	0.01	0.00	0.01	0.45
	(-1.15)	(3.04)	(13.75)	(-0.60)	(0.66)	(0.12)	(0.60)	(-0.34)	(0.14)	(0.12)	(0.72)	
RB	-0.09	0.04***	0.16***	0.00	0.03	0.05**	0.02	-0.02	0.14**	0.00	0.01	0.34
	(-1.22)	(3.79)	(10.84)	(0.09)	(1.24)	(2.14)	(0.77)	(-0.26)	(2.04)	(0.15)	(1.37)	
						Metals						
GC	-0.13***	0.03	0.23***	-0.06*	0.02	0.07***	-0.03	0.02	-0.16**	0.00	0.00	0.39
	(-3.29)	(1.53)	(11.70)	(-1.77)	(0.54)	(3.22)	(-1.37)	(0.43)	(-2.50)	(0.45)	(0.03)	
SI	-0.20***	0.01	0.25***	-0.17***	0.07	-0.02	0.04	-0.16	0.02	-0.00	0.02*	0.23
	(-4.40)	(1.05)	(5.65)	(-3.58)	(1.21)	(-0.50)	(1.25)	(-1.56)	(0.18)	(-0.42)	(1.73)	
PL	-0.10*	0.05	0.14***	-0.27***	-0.06	0.05	-0.04	0.27**	-0.02	0.01	-0.01	0.15
	(-1.71)	(1.61)	(5.18)	(-3.33)	(-0.78)	(0.98)	(-0.88)	(2.01)	(-0.14)	(0.97)	(-0.60)	
PA	-0.12**	0.04***	0.16***	-0.16***	0.05	0.01	0.07**	0.01	-0.07	-0.02***	0.01	0.24
	(-2.31)	(2.77)	(6.56)	(-3.37)	(0.85)	(0.20)	(2.21)	(0.12)	(-0.61)	(-2.75)	(1.43)	
HG	-0.10	0.04	0.14***	-0.08*	0.02	0.02	-0.01	-0.09	-0.27***	-0.01	0.00	0.15
	(-1.57)	(1.51)	(4.86)	(-1.66)	(0.27)	(0.57)	(-0.40)	(-0.86)	(-2.65)	(-1.06)	(0.14)	
						Grains						
C	-0.06	-0.00	0.02*	-0.00	0.03	-0.00	-0.02	-0.09*	-0.02	-0.00	-0.01*	0.02
	(-1.23)	(-0.41)	(1.77)	(-0.06)	(0.98)	(-0.21)	(-1.30)	(-1.66)	(-0.43)	(-0.61)	(-1.73)	
S	-0.02	-0.01	0.13***	-0.08***	-0.03	-0.03	0.00	-0.07	-0.01	-0.00	0.01**	0.23
	(-0.31)	(-1.19)	(10.66)	(-2.75)	(-0.91)	(-1.51)	(0.18)	(-1.17)	(-0.16)	(-0.51)	(2.47)	
W	-0.27***	0.01	0.08***	-0.05	0.05*	-0.01	0.01	-0.13**	0.02	-0.00	0.00	0.17
	(-4.08)	(1.20)	(4.85)	(-1.63)	(1.81)	(-0.40)	(0.35)	(-2.54)	(0.21)	(-0.53)	(0.41)	
KW	-0.02	-0.00	0.09***	-0.06	-0.04	-0.01	0.02	-0.19**	-0.13	0.00	0.01	0.07
	(-0.34)	(-0.35)	(4.84)	(-1.65)	(-1.14)	(-0.28)	(0.83)	(-2.03)	(-1.49)	(0.56)	(1.35)	
MW	-0.07*	0.02	0.30***	-0.04	0.06	-0.05	0.05	0.01	0.16	-0.00	0.01	0.31
	(-1.79)	(1.19)	(13.19)	(-0.58)	(0.95)	(-1.34)	(1.18)	(0.05)	(1.24)	(-0.35)	(1.28)	
O	-0.02	0.01	0.20***	0.02	-0.04	0.06	-0.00	0.13	0.26	-0.01	0.01	0.21
	(-0.41)	(0.40)	(10.38)	(0.23)	(-0.45)	(1.09)	(-0.05)	(0.72)	(1.49)	(-0.60)	(0.37)	
						Food and fiber						
CC	-0.20***	-0.01	0.14***	-0.10***	-0.04	0.04*	0.05**	-0.11	0.09	0.01	0.00	0.31
	(-4.31)	(-1.10)	(6.54)	(-3.27)	(-1.16)	(1.93)	(2.31)	(-1.55)	(1.47)	(1.64)	(0.44)	
CT	-0.15***	0.02*	0.17***	-0.06**	-0.03	0.03	0.02	-0.05	0.09	-0.00	0.00	0.38
	(-3.20)	(1.70)	(14.25)	(-2.06)	(-1.00)	(1.14)	(0.68)	(-0.63)	(1.42)	(-0.01)	(0.38)	
KC	-0.33***	0.01	0.10***	-0.07**	-0.05	-0.00	-0.01	-0.03	-0.08	-0.00	-0.00	0.27
	(-4.75)	(0.98)	(6.07)	(-2.11)	(-1.48)	(-0.07)	(-0.67)	(-0.70)	(-1.35)	(-0.24)	(-0.19)	
JO	-0.19***	-0.01	0.18***	-0.09	-0.07	-0.01	0.04	0.05	0.01	-0.01	-0.00	0.31
	(-3.69)	(-0.36)	(10.18)	(-1.39)	(-1.39)	(-0.17)	(1.09)	(0.39)	(0.12)	(-0.91)	(-0.34)	
SB	-0.14**	0.02*	0.20***	-0.07**	0.03	0.03	0.01	-0.06	0.06	0.01	-0.00	0.33
	(-2.33)	(1.85)	(9.96)	(-2.12)	(0.88)	(1.61)	(0.65)	(-0.78)	(0.88)	(1.08)	(-0.58)	
						Livestock and meats						
FC	0.01	-0.09*	-0.13***	-0.03	-0.11	-0.04	0.07	-0.00	0.20	-0.02	0.00	0.04
	(0.18)	(-1.81)	(-3.17)	(-0.32)	(-1.31)	(-0.64)	(1.19)	(-0.00)	(1.19)	(-1.09)	(0.10)	
LC	-0.02	-0.02	-0.08***	0.05	-0.05	0.04*	-0.02	0.14	-0.02	0.00	-0.01	0.06
	(-0.42)	(-0.85)	(-4.71)	(1.60)	(-1.63)	(1.95)	(-0.81)	(2.30)	(-0.38)	(0.11)	(-1.51)	
LH	-0.07	-0.04***	0.09***	-0.05	-0.01	-0.01	0.02	-0.13	0.02	-0.01	-0.00	0.08
	(-1.22)	(-3.74)	(3.65)	(-1.55)	(-0.29)	(-0.27)	(0.64)	(-1.59)	(0.25)	(-1.27)	(-0.74)	

Note: Table 6 lists all the coefficients and t-statistics in parentheses of equation (7): $\Delta pos_{t,i}^{j} = \alpha_i + \delta_i \Delta pos_{t-1,i}^{j} + \gamma_i r_{t-1,i} + \theta_i \Delta HP_{t,i} + \beta' X + \omega_i D_{FebBreak} + \varepsilon_{t,i}$. Regressions were calculated by OLS, and Newey-West standard errors are calculated for regressions with serial correlated and/or heteroskedastic error terms. CL= WTI Crude Oil, HO=Heating Oil, RB=RBOB Gasoline, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium, HG=Copper, C=Corn, S=Soybeans, W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, O=Oats, CC=Cocoa, CT=Cotton, KC=Coffee, JO=Orange Juice, SB=Sugar, FC=Feeder Cattle, LC=Live Cattle, LH=Lean Hogs; NR(-1)=one lagged non reportables' net long position changes, F(-1)=one lagged futures return, HP=hedging pressure, DI=Dollar Index, DI(-1) one lagged Dollar Index, SP=S&P 500, SP(-1)=one lagged S&P 500, BIUS=Citigroup WGBI US all maturities, BIUS(-1)=one lagged Citigroup WGBI US all maturities, VIX=S&P 500 Volatility Index, VIX(-1)= one lagged S&P 500 Volatility Index, FEB= dummy for February effect. ***, ***, * denote significance at 1, 5 and 10 percent level, respectively.

Table 7a: Futures returns as the dependent variable, the "hedging pressure version"

	F(-1)	HP	HP(-1)	DI	DI(-1)	SP	SP(-1)	BIUS	BIUS(-1)	R² adj.
					Energies					
CL	-0.04 (-0.69)	-0.03 (-0.10)	-0.09 (-0.29)	-1.30*** (-4.96)	-0.29* (-1.69)	0.58*** (3.33)	0.02 (0.10)	-1.92*** (-3.76)	-0.97** (-2.03)	0.33
HO	0.00 (0.03)	0.58*** (9.23)	-0.23*** (-3.38)	-0.99*** (-7.02)	-0.28* (-1.93)	0.39*** (4.17)	0.20** (2.14)	-1.45*** (-5.00)	-0.67** (-2.27)	0.43
RB	-0.01 (-0.24)	0.47*** (6.86)	-0.16** (-2.24)	-0.95*** (-5.54)	-0.16 (-0.93)	0.37*** (3.31)	0.24** (2.11)	-1.94*** (-5.53)	-0.76** (-2.12)	0.33
					Metals					
GC	-0.08 (-1.63)	0.51*** (9.62)	0.00 (0.04)	-0.85*** -6.70)	0.04 (0.39)	0.03 (0.40)	-0.01 (-0.14)	0.56** (2.45)	0.29 (1.44)	0.39
SI	-0.05 (-0.96)	0.68*** (6.87)	0.08 (0.79)	-1.75*** (-9.48)	-0.20 (-1.01)	0.19 (1.61)	-0.04 (-0.31)	-0.22 (-0.58)	-0.28 (-0.76)	0.32
PL	-0.10 (-1.48)	0.25*** (3.60)	0.11** (2.52)	-1.11*** (-4.17)	-0.01 (-0.03)	0.13 (1.14)	0.04 (0.39)	-0.65 (-1.54)	0.24 (0.60)	0.26
PA	-0.06 (-0.93)	0.44*** (6.15)	-0.06 (-0.82)	-0.99*** (-3.80)	0.16 (0.60)	0.36*** (2.78)	0.16 (1.36)	-1.38*** (-3.15)	-0.13 (-0.28)	0.32
HG	0.01 (0.20)	0.50*** (7.60)	-0.06 (-0.98)	-0.74*** (-3.28)	-0.01 (-0.09)	0.38*** (2.88)	-0.04 (-0.35)	-0.88 (-2.24)	-0.14 (-0.31)	0.34
					Grains					
C	-0.08* (-1.76)	1.19*** (13.46)	-0.26*** (-2.60)	-0.69*** (-4.15)	0.03 (0.20)	0.07 (0.65)	0.14 (1.32)	-0.74** (-2.18)	-0.19 (-0.57)	0.37
S	-0.12** (-2.15)	0.67*** (11.86)	-0.05 (-0.91)	-0.54*** (-4.26)	-0.17 (-1.25)	0.08 (0.75)	0.13 (1.61)	-0.73*** (-2.70)	-0.09 (-0.32)	0.37
W	-0.10 (-1.62)	0.98*** (11.05)	-0.03 (-0.37)	-0.66*** (-3.67)	-0.15 (-0.77)	0.20* (1.86)	-0.08 (-0.65)	-0.49 (-1.12)	-0.08 (-0.22)	0.34
KW	-0.11* (-1.86)	0.79*** (9.53)	-0.13* (-1.79)	-0.80*** (-4.80)	-0.23 (-1.21)	0.11 (1.11)	-0.04 (-0.36)	-0.66* (-1.72)	-0.05 (-0.15)	0.33
MW	0.02 (0.15)	0.41*** (6.80)	-0.15* (-1.80)	-0.65*** (-4.16)	-0.11 (-0.64)	0.19* (1.80)	-0.17 (-1.40)	-0.89** (-2.14)	0.34 (0.98)	0.19
O	-0.13*** (-2.66)	0.38*** (8.28)	-0.12*** (-2.60)	-0.93 (-4.54)	-0.10 (-0.47)	-0.02 (-0.15)	0.21 (1.62)	-0.90** (-2.18)	-0.10 (-0.24)	0.24
					Food and fiber					
CC	-0.11** (-2.35)	0.76*** (13.19)	-0.28*** (-4.58)	-0.85*** (-6.04)	-0.05 (-0.37)	0.05 (0.54)	0.08 (0.88)	-0.30 (-1.06)	0.52* (1.84)	0.40
CT	0.03 (0.52)	0.44*** (8.01)	-0.18*** (-3.39)	-0.47*** (-2.90)	-0.31 (-1.45)	0.25** (2.23)	0.06 (0.50)	-0.16 (-0.47)	-0.15 (-0.39)	0.24
KC	0.00 (-0.09)	0.85*** (16.37)	-0.27*** (-4.31)	-0.50*** (-3.41)	-0.04 (-0.30)	0.32 (3.39)	0.02 (0.26)	-0.27 (-0.92)	0.16 (0.54)	0.45
JO	-0.11* (-1.66)	0.63*** (13.13)	-0.19*** (-3.80)	-0.06 (-0.38)	0.05 (0.29)	0.27*** (2.61)	0.16* (1.89)	-0.17 (-0.52)	-0.10 (-0.36)	0.38
SB	-0.09 (-1.34)	0.79*** (7.40)	-0.11 (-0.96)	-0.35* (-1.76)	0.23 (1.14)	0.17 (1.37)	0.13 (1.02)	-0.43 (-1.11)	0.02 (0.06)	0.19
					Livestock and meats					
FC	-0.09* (-1.75)	0.26*** (5.66)	-0.04 (-0.84)	-0.02 (-0.22)	0.06 (0.62)	0.10* (1.72)	0.08 (1.38)	-0.11 (-0.60)	-0.26 (-1.43)	0.08
LC	-0.11** (-2.21)	0.23*** (5.05)	-0.22*** (-4.94)	-0.06 (-0.70)	0.08 (0.97)	0.10 (1.98)	0.09* (1.72)	0.03 (0.17)	-0.14 (-0.87)	0.14
LH	-0.05 (-0.70)	0.68*** (7.78)	-0.37*** (-4.89)	0.11 (0.92)	-0.10 (-0.76)	0.08 (1.05)	-0.05 (-0.54)	0.12 (0.47)	0.12 (0.39)	0.15

Note: Table 7a lists all the coefficients and t-statistics in parentheses of equation (8a): $r_{t,i} = \alpha_i + \gamma_i r_{t-1,i} + \theta_1^{HP} \Delta HP_t + \theta_2^{HP} \Delta HP_{t-1} + \beta' X + \varepsilon_{t,i}$. Regressions were calculated by OLS, and Newey-West standard errors are calculated for regressions with serial correlated and/or heteroskedastic error terms. CL= WTI Crude Oil, HO=Heating Oil, RB=RBOB Gasoline, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium, HG=Copper, C=Corn, S=Soybeans, W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, O=Oats, CC=Cocoa, CT=Cotton, KC=Coffee, JO=Orange Juice, SB=Sugar, FC=Feeder Cattle, LC=Live Cattle, LH=Lean Hogs; F(-1)=one lagged futures return, HP=hedging pressure, HP(-1)=one lagged hedging pressure, DI=Dollar Index, DI(-1) one lagged Dollar Index, SP=S&P 500, SP(-1)=one lagged S&P 500, BIUS=Citigroup WGBI US all maturities, BIUS(-1)=one lagged Citigroup WGBI US all maturities, VIX=S&P 500 Volatility Index, VIX(-1)= one lagged S&P 500 Volatility Index. ***, ***, * denote significance at 1, 5 and 10 percent level, respectively.

Table 7b: Futures returns as the dependent variable, the "money manager version"

	F(-1)	MM	MM(-1)	DI	DI(-1)	SP	SP(-1)	BIUS	BIUS(-1)	R² adj.
					Energies					
CL	-0.04	1.29***	-0.22	-1.06***	-0.21	0.46**	0.09	-1.65***	-0.92**	0.42
	(-0.63)	(6.49)	(-1.37)	(-4.38)	(-1.18)	(2.50)	(0.48)	(-3.12)	(-1.98)	
HO	0.00	0.71***	-0.28***	-0.93***	-0.32**	0.42***	0.19**	-1.32***	-0.71**	0.46
	(-0.08)	(10.55)	(-3.80)	(-6.69)	(-2.22)	(4.66)	(2.05)	(-4.68)	(-2.47)	
RB	-0.02	0.60***	-0.17**	-0.89***	-0.17	0.37***	0.25*	-1.83***	-0.64	0.35
	(-0.28)	(6.27)	(-2.00)	(-3.33)	(-0.90)	(2.61)	(1.77)	(-3.94)	(-1.34)	
					Metals					
GC	-0.05	0.42***	-0.06	-0.84***	0.07	0.01	-0.01	0.43**	0.29	0.42
	(-1.09)	(11.64)	(-1.41)	(-8.56)	(0.69)	(0.20)	(-0.09)	(2.23)	(1.49)	
SI	-0.05	0.79***	-0.14*	-1.69***	-0.13	0.09	0.01	-0.33	-0.09	0.42
	(-0.96)	(11.51)	(-1.90)	(-9.98)	(-0.71)	(0.80)	(0.08)	(-0.96)	(-0.25)	
PL	-0.08	0.27***	0.03	-1.08***	-0.01	0.15	0.05	-0.53	0.10	0.28
	(-1.08)	(5.19)	(0.60)	(-4.42)	(-0.04)	(1.34)	(0.52)	(-1.33)	(0.25)	
PA	-0.03	0.38***	-0.08	-1.02***	0.12	0.33**	0.18	-1.38***	-0.06	0.32
	(-0.45)	(5.57)	(-1.32)	(-3.68)	(0.45)	(2.44)	(1.42)	(-3.05)	(-0.11)	
HG	0.06	0.45***	-0.13***	-0.74***	0.04	0.39***	-0.05	-0.74*	-0.15	0.41
	(0.95)	(8.75)	(-3.84)	(-3.28)	(0.23)	(2.86)	(-0.43)	(-1.88)	(-0.34)	
					Grains					
C	-0.13***	1.25***	-0.26**	-0.72***	0.07	0.09	0.12	-0.95***	0.14	0.36
	(-2.79)	(13.10)	(-2.50)	(-4.28)	(0.41)	(0.86)	(1.12)	(-2.78)	(0.40)	
S	-0.11*	0.73***	-0.09	-0.54***	-0.15	0.11	0.09	-0.74***	-0.05	0.34
	(-1.96)	(11.80)	(-1.40)	(-4.27)	(-1.04)	(0.97)	(1.10)	(-2.81)	(-0.18)	
W	-0.12**	0.91***	0.00	-0.80***	-0.17	0.22*	-0.08	-0.48	0.08	0.32
	(-2.17)	(9.90)	(-0.06)	(-4.26)	(-0.86)	(1.89)	(-0.61)	(-1.12)	(0.21)	
KW	-0.13**	0.87***	-0.15**	-0.79***	-0.24	0.18	-0.10	-0.56	-0.01	0.31
	(-2.19)	(10.67)	(-2.03)	(-4.67)	(-1.23)	(1.46)	(-0.85)	(-1.44)	(-0.03)	
MW	0.03	0.46***	-0.15	-0.63***	-0.10	0.18*	-0.15	-0.89**	0.30	0.15
	(0.35)	(5.37)	(-1.28)	(-3.94)	(-0.55)	(1.68)	(-1.24)	(-2.08)	(0.90)	
O	-0.17***	0.63***	-0.13**	-0.96***	-0.04	0.06	0.16	-0.79**	-0.29	0.35
	(-3.58)	(12.43)	(-2.35)	(-5.15)	(-0.21)	(0.50)	(1.34)	(-2.05)	(-0.77)	
					Food and fiber					
CC	-0.15***	0.71***	-0.25***	-1.00***	-0.04	0.11	0.12	-0.32	0.51*	0.33
	(-3.13)	(10.73)	(-3.85)	(-6.83)	(-0.27)	(1.22)	(1.24)	-(1.06)	(1.70)	
CT	-0.01	0.54***	-0.19***	-0.45***	-0.32	0.25**	0.07	-0.27	-0.30	0.23
	(-0.21)	(8.20)	(-3.53)	(-2.70)	(-1.48)	(2.14)	(0.52)	(-0.73)	(-0.77)	
KC	-0.07	0.92***	-0.31***	-0.60***	0.03	0.24***	-0.01	-0.36	0.04	0.46
	(-1.19)	(14.67)	(-4.53)	(-4.51)	(0.17)	(3.07)	(-0.17)	(-1.58)	(0.15)	
JO	-0.21***	0.78***	-0.25***	0.01	-0.11	0.28***	0.10	-0.07	-0.33	0.45
	(-3.42)	(14.59)	(-6.04)	(0.09)	(-0.78)	(2.84)	(1.05)	(-0.21)	(-1.17)	
SB	-0.14**	1.15***	-0.22**	-0.40**	0.14	0.19	0.05	-0.35	0.00	0.22
	(-2.40)	(8.86)	(-2.03)	(-2.02)	(0.73)	(1.57)	(0.35)	(-0.96)	(0.01)	
					Livestock and meats					
FC	-0.09*	0.25***	-0.09***	-0.02	0.04	0.11*	0.10*	-0.16	-0.22	0.14
	(-1.79)	(7.91)	(-2.90)	(-0.25)	(0.46)	(1.89)	(1.73)	(-0.91)	(-1.27)	
LC	-0.15***	0.33***	-0.22***	-0.05	0.04	0.11**	0.10**	0.07	-0.14	0.18
	(-3.20)	(7.46)	(-5.18)	(-0.62)	(0.55)	(2.33)	(2.00)	(0.42)	(-0.92)	
LH	-0.13*	0.71***	-0.19**	0.06	-0.08	0.06	-0.04	0.10	0.12	0.16
	(-1.89)	(8.48)	(-2.58)	(0.45)	(-0.66)	(0.75)	(-0.49)	(0.40)	(0.38)	

Note: Table 7b lists all the coefficients and t-statistics in parentheses of equation (8b): $r_{t,i} = \alpha_i + \gamma_i r_{t-1,i} + \theta_1^{MM} \Delta MM_t + \theta_2^{MM} \Delta MM_{t-1} + \beta' X + \varepsilon_{t,i}$. Regressions were calculated by OLS, and Newey-West standard errors are calculated for regressions with serial correlated and/or heteroskedastic error terms. CL= WTI Crude Oil, HO=Heating Oil, RB=RBOB Gasoline, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium, HG=Copper, C=Corn, S=Soybeans, W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, O=Oats, CC=Cocoa, CT=Cotton, KC=Coffee, JO=Orange Juice, SB=Sugar, FC=Feeder Cattle, LC=Live Cattle, LH=Lean Hogs; F(-1)=one lagged futures return, MM= speculative pressure, MM(-1)=one lagged speculative pressure, DI=Dollar Index, DI(-1) one lagged Dollar Index, SP=S&P 500, SP(-1)=one lagged S&P 500, BIUS=Citigroup WGBI US all maturities, BIUS(-1)=one lagged Citigroup WGBI US all maturities, VIX=S&P 500 Volatility Index, VIX(-1)= one lagged S&P 500 Volatility Index. ***, ***, * denote significance at 1, 5 and 10 percent level, respectively.

Table 8a: Errors of 8a "hedging pressure version" as the dependent variable

	MM			SW			OR			NR		
	POS	POS(-1)	R^2 adj.	POS	POS(-1)	R^2 adj.	POS	POS (-1)	R^2 adj.	POS	POS(-1)	R^2 adj.
						Energies						
CL	1.13***	-0.24	0.12	-0.89***	0.22	0.06	-0.10	0.22	-0.00	-1.83***	-0.54	0.05
	(7.78)	(-1.64)		(-5.35)	(1.36)		(-0.47)	(1.05)		(-5.16)	(-1.53)	
HO	0.19***	-0.07	0.02	-0.83***	0.13	0.08	-0.49***	0.04	0.02	0.39***	0.06	0.02
	(3.04)	(-1.12)		(-6.47)	(1.04)		(-3.26)	(0.24)		(2.93)	(0.44)	
RB	0.12*	-0.03	0.00	-0.64***	-0.02	0.02	-0.83***	0.14	0.03	0.49**	0.13	0.01
	(1.69)	(-0.36)		(-3.39)	(-0.12)		(-3.77)	(0.66)		(2.39)	(0.66)	
						Metals						
GC	0.13***	-0.06	0.03	-0.24***	0.07	0.05	-0.26***	0.07	0.02	0.39***	0.08	0.02
	(3.86)	(-1.62)		(-5.01)	(1.48)		(-3.25)	(0.83)		(3.60)	(0.76)	
SI	0.46***	-0.20***	0.09	-0.74***	0.17	0.10	-0.92***	0.07	0.07	0.28*	0.13	0.00
	(6.85)	(-2.95)		(-7.24)	(1.62)		(-5.88)	(0.45)		(1.81)	(0.86)	
PL	0.13***	-0.04	0.02	-0.20***	-0.05	0.04	-0.02	0.07	0.00	0.19**	0.16*	0.01
	(3.26)	(-0.99)		(-4.47)	(-1.01)		(-0.27)	(0.97)		(2.21)	(1.81)	
PA	0.16***	-0.07	0.02	-0.43***	0.12**	0.11	0.20**	-0.08	0.01	0.69***	-0.02	0.05
	(3.11)	(-1.31)		(-7.27)	(2.11)		(1.98)	(-0.80)		(4.77)	(-0.14)	
HG	0.19***	-0.11**	0.05	-0.27***	0.06	0.03	-0.27***	0.24***	0.04	-0.18	0.02	0.00
	(4.57)	(-2.58)		(-3.73)	(0.82)		(-3.19)	(2.88)		(-1.47)	(0.15)	
						Grains						
C	0.19**	-0.06	0.01	-1.03***	-0.04	0.07	-0.17	0.22	0.00	1.19***	0.59**	0.04
	(2.08)	(-0.62)		(-5.71)	(-0.24)		(-0.79)	(0.99)		(3.99)	(1.98)	
S	0.06	-0.04	0.00	-0.56***	0.16	0.04	-0.18	0.15	0.00	1.03***	-0.20	0.08
	(1.02)	(-0.62)		(-4.71)	(1.36)		(-1.49)	(1.19)		(6.09)	(-1.16)	
W	0.11	0.01	0.00	-0.54***	-0.07	0.03	0.01	0.19	0.00	0.74***	-0.02	0.01
	(1.41)	(0.14)		(-3.94)	(-0.54)		(0.04)	(1.09)		(2.63)	(-0.08)	
KW	0.13	-0.09	0.00	-0.54***	0.02	0.02	-0.53***	0.13	0.02	0.69***	0.14	0.03
	(1.63)	(-1.10)		(-3.50)	(0.15)		(-3.08)	(0.76)		(3.94)	(0.82)	
MW	0.06	-0.06	0.00	0.16	0.35	0.00	-0.21*	-0.08	0.00	0.05	0.07	0.00
	(0.65)	(-0.65)		(0.59)	(1.27)		(-1.72)	(-0.67)		(0.50)	(0.63)	
O	0.30***	-0.08*	0.07	-0.38***	0.05	0.02	-0.48***	0.18**	0.06	-0.19*	-0.10	0.01
	(5.94)	(-1.70)		(-3.53)	(0.49)		(-5.48)	(2.09)		(-1.95)	(-1.06)	
						Food and fiber						
CC	0.03	-0.05	0.00	0.04	0.07	0.00	-0.85***	0.49***	0.07	0.75***	-0.11	0.04
	(0.43)	(-0.84)		(0.26)	(0.43)		(-5.13)	(2.95)		(4.37)	(-0.65)	
CT	0.10*	-0.02	0.00	-0.54***	0.15	0.06	0.03	0.05	0.00	0.62***	-0.19	0.03
	(1.67)	(-0.36)		(-5.48)	(1.55)		(0.24)	(0.39)		(3.74)	(-1.14)	
KC	0.14***	-0.10**	0.01	-0.71***	0.30**	0.07	-0.16	0.17	0.00	0.34	0.29	0.00
	(2.64)	(-1.98)		(-5.75)	(2.53)		(-1.14)	(1.21)		(1.61)	(1.39)	
JO	0.18***	-0.10**	0.04	-0.81***	0.33*	0.05	-0.67***	0.21***	0.17	0.52***	0.04	0.04
	(4.32)	(-2.42)		(-4.67)	(1.91)		(-9.44)	(2.96)		(4.69)	(0.40)	
SB	0.31***	-0.14	0.01	-1.14***	0.30**	0.12	-0.72***	0.27	0.02	1.44***	-0.04	0.10
	(2.88)	(-1.26)		(-7.69)	(2.06)		(-2.94)	(1.12)		(7.11)	(-0.20)	
						Livestock and meats						
FC	0.13***	-0.10***	0.05	-0.10	0.04	0.00	-0.12**	0.08*	0.02	-0.15***	0.07	0.02
	(4.52)	(-3.32)		(-1.24)	(0.53)		(-2.46)	(1.67)		(-3.02)	(1.49)	
LC	0.15***	-0.08*	0.03	-0.48***	0.28***	0.08	-0.08	0.00	0.00	-0.07	-0.11	0.00
	(3.54)	(-1.81)		(-5.55)	(3.32)		(-1.12)	(-0.05)		(-0.54)	(-0.89)	
LH	0.26***	-0.08	0.03	-0.78***	0.20*	0.11	-0.23**	-0.18	0.01	0.88***	0.13	0.05
	(3.73)	(-1.17)		(-7.38)	(1.92)		(-2.09)	(-1.62)		(5.24)	(0.75)	

Note: Table 8a lists all the coefficients and t-statistics in parentheses of equation (9): $\varepsilon_t = \alpha + \delta_1 \Delta pos_{t,j} + \delta_2 \Delta pos_{t-1,j} + u_t$. Regressions were calculated by OLS, and Newey-West standard errors are calculated for regressions with serial correlated and/or heteroskedastic error terms. CL= WTI Crude Oil, HO=Heating Oil, RB=RBOB Gasoline, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium, HG=Copper, C=Corn, S=Soybeans, W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, O=Oats, CC=Cocoa, CT=Cotton, KC=Coffee, JO=Orange Juice, SB=Sugar, FC=Feeder Cattle, LC=Live Cattle, LH=Lean Hogs; MM=money managers, SW=swap dealers, OR=other reportables, NR=non-reportables; POS=contemporaneous position change of corresponding trader's category, POS(-1)=one lagged position change of corresponding trader's category. ***, ***, * denote significance at 1, 5 and 10 percent level, respectively.

Table 8b: Errors of 8b "speculative pressure version" as the dependent variable

	HP			SW			OR			NR		
	POS	POS(-1)	R^2 adj.	POS	POS (-1)	R^2 adj.	POS	POS(-1)	R^2 adj.	POS	POS(-1)	R^2 adj.
						Energies						
CL	-0.64***	0.10	0.02	-0.27*	0.00	0.00	0.41**	0.13	0.01	-1.35***	-0.22	0.03
	(-2.97)	(0.46)		(-1.71)	(0.00)		(2.08)	(0.66)		(-4.06)	(-0.65)	
HO	0.06	-0.07	0.00	-0.30**	-0.05	0.01	0.10	-0.16	0.00	0.55***	-0.19	0.04
	(1.10)	(-1.20)		(-2.31)	(-0.35)		(0.66)	(-1.09)		(4.28)	(-1.50)	
RB	0.02	-0.02	0.00	-0.17	-0.14	0.00	-0.33	0.08	0.00	0.68***	-0.07	0.02
	(0.30)	(-0.39)		(-0.92)	(-0.76)		(-1.52)	(0.37)		(3.37)	(-0.33)	
						Metals						
GC	0.10**	0.01	0.01	0.02	-0.01	0.00	0.00	0.05	0.00	0.45***	0.13	0.04
	(2.19)	(0.31)		(0.51)	(-0.22)		(0.00)	(0.59)		(4.37)	(1.23)	
SI	0.03	0.11	0.00	-0.19*	0.05	0.00	-0.10	0.16	0.00	0.62***	0.23*	0.04
	(0.38)	(1.26)		(-1.91)	(0.54)		(-0.67)	(1.05)		(4.46)	(1.65)	
PL	0.06	0.05	0.00	-0.05	-0.03	0.00	0.11	0.09	0.00	0.26***	0.18**	0.03
	(1.40)	(1.14)		(-1.11)	(-0.56)		(1.58)	(1.28)		(3.10)	(2.09)	
PA	0.17***	-0.04	0.01	-0.18***	0.08	0.02	0.47***	-0.11	0.06	0.86***	-0.08	0.07
	(2.76)	(-0.69)		(-2.96)	(1.39)		(4.85)	(-1.08)		(6.02)	(-0.55)	
HG	0.04	0.03	0.00	0.01	0.00	0.00	0.04	0.11	0.00	0.05	-0.09	0.00
	(0.68)	(0.45)		(0.20)	(-0.01)		(0.52)	(1.36)		(0.40)	(-0.77)	
						Grains						
C	0.22**	-0.11	0.01	-0.17	-0.41**	0.01	0.84***	0.09	0.03	1.82***	0.52*	0.08
	(2.56)	(-1.28)		(-0.91)	(-2.17)		(3.85)	(0.40)		(6.23)	(1.76)	
S	0.13***	-0.01	0.01	-0.15	0.16	0.00	0.34***	0.07	0.01	1.32***	-0.26	0.12
	(2.62)	(-0.23)		(-1.17)	(1.26)		(2.65)	(0.54)		(7.74)	(-1.49)	
W	0.21***	-0.08	0.01	0.14	-0.16	0.00	0.43**	0.17	0.01	1.05***	-0.09	0.03
	(2.66)	(-1.01)		(0.97)	(-1.16)		(2.46)	(0.94)		(3.67)	(-0.33)	
KW	0.17**	-0.06	0.01	-0.08	0.03	0.00	0.13	-0.02	0.00	1.17***	0.06	0.09
	(2.49)	(-0.81)		(-0.52)	(0.16)		(0.72)	(-0.09)		(6.83)	(0.37)	
MW	0.19***	-0.10	0.02	0.50*	0.19	0.00	0.12	-0.21*	0.00	0.40***	-0.06	0.03
	(3.24)	(-1.65)		(1.79)	(0.70)		(0.99)	(-1.69)		(3.76)	(-0.56)	
O	0.02	-0.03	0.00	-0.01	-0.07	0.00	-0.06	0.13	0.00	0.13	-0.25***	0.02
	(0.56)	(-0.88)		(-0.14)	(-0.74)		(-0.69)	(1.59)		(1.50)	(-2.81)	
						Food and fiber						
CC	0.21***	-0.10*	0.03	0.74***	-0.18	0.03	-0.25	0.19	0.00	1.45***	-0.30*	0.15
	(3.65)	(-1.83)		(4.15)	(-1.02)		(-1.36)	(1.05)		(8.61)	(-1.77)	
CT	0.11***	-0.07	0.01	-0.15	0.00	0.00	0.45***	-0.09	0.03	0.82***	-0.42**	0.06
	(2.29)	(-1.56)		(-1.46)	(-0.02)		(3.72)	(-0.73)		(5.02)	(-2.56)	
KC	0.12**	-0.04	0.01	0.02	0.12	0.00	0.52***	-0.15	0.03	0.74***	0.01	0.03
	(2.42)	(-0.79)		(0.18)	(0.96)		(3.84)	(-1.06)		(3.60)	(0.07)	
JO	0.07***	-0.02	0.00	-0.10	0.13	0.00	-0.06	0.02	0.00	0.75***	-0.06	0.11
	(1.92)	(-0.65)		(-0.61)	(0.81)		(-0.75)	(0.28)		(7.38)	(-0.59)	
SB	0.11	-0.02	0.00	-0.49***	0.24	0.02	0.03	0.13	0.00	1.63***	-0.19	0.13
	(1.42)	(-0.21)		(-3.18)	(1.57)		(0.12)	(0.54)		(8.35)	(-0.97)	
						Livestock and meats						
FC	0.05	0.02	0.00	0.01	0.08	0.00	0.07	0.02	0.00	0.01	0.01	0.00
	(1.30)	(0.47)		(0.16)	(0.99)		(1.48)	(0.35)		(0.12)	(0.12)	
LC	0.01	-0.07	0.00	-0.28***	0.10	0.02	0.15**	-0.18***	0.02	0.07	-0.12	0.00
	(0.26)	(-1.64)		(-3.30)	(1.15)		(2.20)	(-2.77)		(0.57)	(-0.99)	
LH	0.22***	-0.22***	0.02	-0.35***	0.01	0.02	0.26**	-0.34***	0.03	1.09***	0.06	0.09
	(2.94)	(-2.99)		(-3.14)	(0.07)		(2.38)	(-3.18)		(6.61)	(0.38)	

Note: Table 8b lists all the coefficients and t-statistics in parentheses of equation (9): $\varepsilon_t = \alpha + \delta_1 \Delta pos_{t,j} + \delta_2 \Delta pos_{t-1,j} + u_t$. Regressions were calculated by OLS, and Newey-West standard errors are calculated for regressions with serial correlated and/or heteroskedastic error terms. CL= WTI Crude Oil, HO=Heating Oil, RB=RBOB Gasoline, GC=Gold, SI=Silver, PL=Platinum, PA=Palladium, HG=Copper, C=Corn, S=Soybeans, W=CBOT Wheat, KW=Kansas City Wheat, MW=Minneapolis Wheat, O=Oats, CC=Cocoa, CT=Cotton, KC=Coffee, JO=Orange Juice, SB=Sugar, FC=Feeder Cattle, LC=Live Cattle, LH=Lean Hogs; HP=hedging pressure, SW=swap dealers, OR=other reportables, NR=non-reportables; POS=contemporaneous position change of corresponding trader's category, POS(-1)=one lagged position change of corresponding trader's category. ***, ***, * denote significance at 1, 5 and 10 percent level, respectively.

Table A.1: Correlations between DCOT trader categories

crude oil	HP	MM	SW	OR	NR
HP	1				
MM	0,326	1			
SW	0,187	**-0,544**	1		
OR	0,155	-0,302	-0,275	1	
NR	0,099	-0,120	-0,138	-0,181	1

heating oil	HP	MM	SW	OR	NR
HP	1				
MM	**0,819**	1			
SW	-0,028	-0,385	1		
OR	-0,074	**-0,408**	0,081	1	
NR	**0,664**	**0,520**	-0,329	-0,271	1

gasoline	HP	MM	SW	OR	NR
HP	1				
MM	**0,867**	1			
SW	0,203	-0,147	1		
OR	-0,068	-0,361	0,132	1	
NR	**0,549**	0,399	-0,139	-0,263	1

gold	HP	MM	SW	OR	NR
HP	1				
MM	**0,747**	1			
SW	-0,274	**-0,702**	1		
OR	0,050	-0,211	-0,184	1	
NR	**0,575**	**0,488**	**-0,444**	-0,132	1

silver	HP	MM	SW	OR	NR
HP	1				
MM	**0,630**	1			
SW	-0,218	**-0,667**	1		
OR	0,059	**-0,422**	0,098	1	
NR	**0,417**	0,100	-0,370	-0,042	1

platinum	HP	MM	SW	OR	NR
HP	1				
MM	**0,596**	1			
SW	-0,005	**-0,574**	1		
OR	0,260	-0,067	-0,273	1	
NR	0,314	0,150	-0,324	-0,088	1

palladium	HP	MM	SW	OR	NR
HP	1				
MM	**0,611**	1			
SW	-0,061	**-0,620**	1		
OR	0,284	-0,094	-0,267	1	
NR	0,397	0,246	-0,373	0,100	1

copper	HP	MM	SW	OR	NR
HP	1				
MM	**0,749**	1			
SW	-0,013	**-0,412**	1		
OR	-0,363	**-0,652**	-0,068	1	
NR	0,336	0,149	-0,374	-0,092	1

corn	HP	MM	SW	OR	NR
HP	1				
MM	**0,843**	1			
SW	0,292	-0,038	1		
OR	0,158	-0,167	-0,118	1	
NR	0,087	-0,054	-0,286	-0,001	1

soybeans	HP	MM	SW	OR	NR
HP	1				
MM	**0,863**	1			
SW	0,230	-0,033	1		
OR	0,102	-0,214	-0,208	1	
NR	**0,462**	0,373	-0,259	-0,066	1

wheat (CBOT)	HP	MM	SW	OR	NR
HP	1				
MM	**0,835**	1			
SW	0,352	-0,037	1		
OR	-0,269	**-0,485**	-0,274	1	
NR	0,297	0,215	-0,168	-0,227	1

wheat (KCBOT)	HP	MM	SW	OR	NR
HP	1				
MM	**0,845**	1			
SW	0,331	0,080	1		
OR	0,128	-0,191	-0,111	1	
NR	0,269	0,058	-0,278	-0,058	1

wheat (MGEX)	HP	MM	SW	OR	NR
HP	1				
MM	**0,720**	1			
SW	0,204	0,042	1		
OR	0,335	-0,088	-0,034	1	
NR	**0,554**	0,109	-0,040	-0,118	1

oats	HP	MM	SW	OR	NR
HP	1				
MM	**0,720**	1			
SW	0,363	-0,021	1		
OR	0,139	-0,296	-0,076	1	
NR	**0,471**	0,092	0,074	-0,128	1

cocoa	HP	MM	SW	OR	NR
HP	1				
MM	**0,869**	1			
SW	0,199	-0,114	1		
OR	-0,061	-0,337	-0,034	1	
NR	**0,487**	0,218	0,067	-0,102	1

cotton	HP	MM	SW	OR	NR
HP	1				
MM	**0,795**	1			
SW	0,379	-0,056	1		
OR	0,102	-0,280	-0,048	1	
NR	**0,597**	**0,520**	-0,091	-0,106	1

coffee	HP	MM	SW	OR	NR
HP	1				
MM	**0,860**	1			
SW	0,274	-0,098	1		
OR	-0,154	**-0,445**	-0,024	1	
NR	**0,422**	0,298	-0,087	-0,203	1

orange	HP	MM	SW	OR	NR
HP	1				
MM	**0,836**	1			
SW	0,144	-0,107	1		
OR	0,012	**-0,439**	0,142	1	
NR	**0,519**	0,365	-0,099	-0,265	1

sugar	HP	MM	SW	OR	NR
HP	1				
MM	**0,793**	1			
SW	0,387	-0,061	1		
OR	0,024	-0,263	-0,063	1	
NR	**0,563**	**0,437**	-0,142	-0,174	1

feeder cattle	HP	MM	SW	OR	NR
HP	1				
MM	**0,676**	1			
SW	0,183	-0,071	1		
OR	0,151	-0,323	-0,082	1	
NR	-0,194	**-0,527**	-0,172	-0,218	1

live cattle	HP	MM	SW	OR	NR
HP	1				
MM	**0,759**	1			
SW	0,304	-0,046	1		
OR	0,215	-0,271	-0,072	1	
NR	-0,249	-0,312	-0,257	-0,238	1

lean hogs	HP	MM	SW	OR	NR
HP	1				
MM	**0,705**	1			
SW	0,143	-0,255	1		
OR	0,168	-0,298	-0,162	1	
NR	0,189	0,045	-0,284	-0,137	1

Note: HP=hedging pressure, MM=money managers, SW=swap dealers, OR=other reportables, NR=non reportables. All correlations > 0.4 are bold.

Selbstständigkeitserklärung

Diese Dissertation beruht auf fünf Artikeln, die aus meiner Tätigkeit am Institut für Finanzierung resultieren. Der erste Artikel „The Impact of Speculation on Precious Metals Futures Markets" und der zweite Artikel „Price Discovery and Trading Activity in Commodity Futures Markets" sind in gemeinsamer Forschungsarbeit mit Frau M. Sc. Elina Pradkhan entstanden. Der fünfte Artikel „Traders' Motivation and Hedging Pressure in Commodity Futures Markets" ist in gemeinsamer Forschungsarbeit mit Herrn Prof. Kamal Smimou entstanden.

Ich habe die vorliegende Dissertation selbstständig und ohne unzulässige Hilfe Dritter verfasst. Die statistischen Auswertungen wurden mit den Computerprogrammen Eviews und Stata durchgeführt, die Dissertation wurde in MS-Word erstellt. Außer diesen Computerprogrammen und der angeführten Literatur habe ich keine weiteren Hilfsmittel genutzt.

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

David Bosch